



Integrating Trust Persistence with Reliability Modelling for Failure-Adaptive Distributed Cloud Systems

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Abstract: Distributed cloud computing environments suffer from frequent node failures, dynamic workload variations, and trust uncertainty, which collectively degrade system reliability and service availability. Existing studies largely treat reliability modelling (e.g., failure-rate-based approaches) and trust management (e.g., reputation systems) as independent mechanisms, leading to inefficient task allocation and delayed failure recovery in large-scale distributed systems.

This paper proposes a unified failure-adaptive framework that integrates trust persistence with probabilistic reliability modelling to enable intelligent and resilient cloud operations. Unlike conventional approaches, the proposed model introduces two novel components: (i) a persistence-aware trust formulation incorporating Behavioral Consistency Coefficient (BCC) and Recovery Efficiency Score (RES), and (ii) a trust-augmented reliability function that dynamically adjusts node reliability based on long-term behavioral stability.

The key contributions of this paper are as follows:

1. A multi-dimensional trust model incorporating both short-term performance and long-term behavioral stability.
2. A unified mathematical formulation integrating trust persistence with exponential reliability modelling.
3. A failure-adaptive task allocation mechanism that prioritizes nodes based on combined trust-reliability scores.
4. A conceptual self-healing architecture enabling real-time fault detection, isolation, and workload redistribution.

By embedding trust persistence into reliability estimation, the proposed framework enables proactive failure handling, reduces trust oscillation, and improves system resilience. The model is particularly suitable for large-scale, heterogeneous cloud environments where node behavior is uncertain and dynamically evolving. The proposed model is analytically evaluated and validated using simulated reliability-trust scenarios.

Key Words: Distributed Cloud Computing, Trust Persistence, Reliability Modelling, Failure-Adaptive Systems, Trust-Aware Scheduling, Fault Tolerance.

I. INTRODUCTION

Distributed cloud computing has emerged as a critical paradigm for delivering scalable, on-demand computational resources across geographically dispersed infrastructures. Modern cloud systems consist of interconnected nodes, virtual machines, micro services, and data centres that collaboratively support large-scale applications. While this distributed architecture enhances scalability and flexibility, it also introduces inherent challenges such as frequent node failures, performance variability, and uncertainty in node behavior.

In large-scale cloud environments, failures are inevitable due to hardware degradation, network instability, software faults, and dynamic workload fluctuations (Rehman et al., 2022; Kumari and Kaur, 2021). Traditional reliability modelling techniques, which are primarily based on failure rate estimation and probabilistic analysis, provide a quantitative measure of system dependability. However, these models typically assume static system behavior and do not account for the dynamic and heterogeneous nature of distributed cloud infrastructures (Mesbahi et al., 2018).

Parallel to reliability modelling, trust management has gained significant attention as a mechanism to evaluate the credibility and behavior of nodes in distributed systems (Li et al., 2020; Khan et al., 2022). Trust models generally rely on metrics such as reputation, feedback aggregation, and historical performance. Although effective in identifying unreliable or malicious nodes, most existing approaches focus on short-term observations and fail to capture long-term behavioral stability. This limitation leads to trust oscillation, inaccurate node selection, and inefficient task allocation.

A critical limitation in existing research is the separation of reliability modelling and trust evaluation into independent domains. Reliability models focus on failure probability, while trust models address behavioral credibility. The lack of integration between these two dimensions results in suboptimal decision-making, particularly in failure-prone and highly dynamic environments (Zhang et al., 2023).

To address this gap, this paper proposes a unified failure-adaptive framework that integrates trust persistence with reliability modelling. The concept of trust persistence emphasizes long-term behavioural consistency of nodes, enabling the system to distinguish between transient failures and persistent unreliability. The proposed model introduces novel parameters, including

Behavioural Consistency Coefficient (BCC) and Recovery Efficiency Score (RES), to capture long-term stability and post-failure recovery capability.

Furthermore, the framework incorporates a trust-augmented reliability function that dynamically adjusts reliability estimation based on trust persistence. This integration enables intelligent, risk-aware task allocation and supports proactive failure handling. The system continuously monitors node behaviour, detects anomalies, and dynamically redistributes workloads to maintain service continuity.

The main contributions of this paper are summarized as follows:

- Development of a multi-dimensional trust model incorporating long-term behavioural persistence
- Integration of trust persistence with probabilistic reliability modelling
- Design of a failure-adaptive task allocation mechanism based on combined trust–reliability evaluation
- Conceptualization of a self-healing cloud architecture supporting dynamic fault detection and recovery

The remainder of the paper is organized as follows: Section 2 reviews related work, Section 3 presents the proposed system model, Sections 4, 5 and 6 describe trust, persistence and reliability modelling respectively, and Section 7 concludes the paper with results.

II.LITERATURE REVIEW

Research in distributed cloud computing has extensively explored fault tolerance, reliability modelling, and trust management as independent domains. Reliability modelling techniques traditionally rely on probabilistic approaches such as failure rate analysis, Mean Time between Failures (MTBF), and Mean Time to Repair (MTTR) to evaluate system availability. While these models provide a quantitative foundation, they often assume static conditions and fail to capture the dynamic and heterogeneous behavior of modern distributed cloud environments.

Recent studies (2020–2025) have emphasized adaptive fault tolerance mechanisms, including dynamic resource allocation, predictive failure detection, and self-healing architectures. These approaches improve system resilience but primarily focus on structural recovery rather than behavioral evaluation of nodes.

In parallel, trust management models have been developed to assess node credibility using reputation systems, feedback aggregation, and behavioral analysis. Modern trust frameworks incorporate machine learning and anomaly detection to identify malicious or unreliable nodes. However, most existing trust models emphasize short-term observations and lack mechanisms to capture long-term behavioral stability, resulting in trust fluctuation and inconsistent decision-making.

Study	Focus Area	Methodology	Limitation
Bala & Chana (2021)	Fault Tolerance	Redundancy replication	No trust integration
Rehman et al. (2022)	Reliability	Probabilistic modelling	Static assumptions
Li et al. (2020)	Trust Management	Reputation-based model	Short-term focus
Zhang et al. (2021)	Cloud Reliability	MTBF/MTTR models	No behavioral factors
Recent ML-Based models (2023)	Trust Prediction	Machine learning	Lack of persistence modelling

Table 1: Comparative Analysis of Representative Studies

A critical limitation observed across existing literature is the lack of integration between trust modelling and reliability evaluation. Reliability models focus on failure probability, while trust models evaluate behavioral credibility. The absence of a unified Framework leads to inefficient task allocation, delayed failure response, and reduced system performance in dynamic cloud environments. Table 1 presents a comparative analysis of representative studies and highlights their limitations.

From the above analysis, it is evident that existing approaches either focus on reliability or trust independently, without addressing their combined impact on system performance. Furthermore, long-term trust persistence and adaptive failure handling remain underexplored.

To overcome these limitations, this paper proposes a unified framework that integrates trust persistence with reliability modelling in a failure-adaptive distributed cloud environment. The proposed approach introduces novel trust parameters, including Behavioral Consistency Coefficient (BCC) and Recovery Efficiency Score (RES), and combines them with reliability functions to enable intelligent and resilient task allocation.

III.SYSTEM MODEL

This section presents the proposed failure-adaptive distributed cloud system model, which integrates trust persistence with reliability modelling. The design is based on the original conceptual flow of task allocation controlled through trust evaluation and reliability estimation, but is refined to provide clearer structure, technical depth, and implement ability.

The system operates in a distributed cloud environment consisting of multiple interconnected nodes (servers/virtual machines). Each node is continuously evaluated based on its trust behavior and reliability characteristics before being selected for task execution.

3.1 Conceptual Flow of the Model

The original system model follows a logical flow where tasks are assigned based on trust persistence and reliability evaluation. This flow is preserved and structured as follows:

1. Task Submission: Users submit computational tasks to the cloud environment.
2. Resource Pool Identification: Available nodes/resources are identified.
3. Trust Evaluation: Each node is evaluated using trust parameters such as past performance, failure history, and behavioral consistency.
4. Reliability Estimation: Reliability of each node is computed using failure rate models.
5. Decision Making: Nodes are ranked based on combined trust and reliability scores.
6. Task Allocation: Tasks are assigned to the most suitable nodes.
7. Continuous Monitoring: Node performance is continuously monitored.

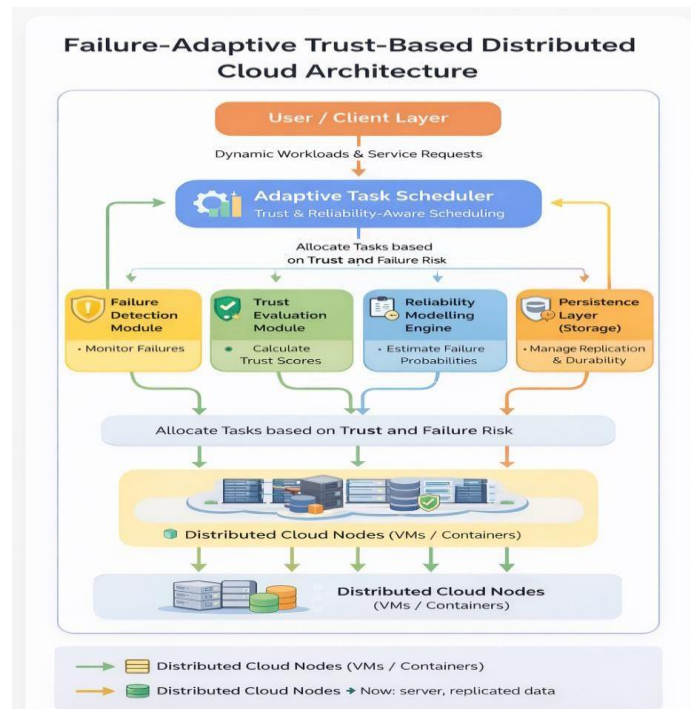


Figure 1: Failure-Adaptive Trust-Reliability System Model

8. Failure Detection: Any abnormal behavior or failure is detected in real time.
9. Task Reallocation: Tasks from failed nodes are reassigned to alternative trusted nodes.

This sequential flow ensures intelligent, adaptive, and resilient task execution. The overall system workflow is illustrated in Figure 1.

3.2. Integrated Trust-Reliability Decision Model

In the original model, trust and reliability are conceptually combined. Here, this integration is formalized for clarity. The combined decision score is defined as:

$$\text{Score}(n) = \alpha \times T(n) + \beta \times R(n)$$

Where:

$T(n)$ = Trust score of node n $R(n)$ = Reliability of node n

α and β are weighting factors such that $\alpha + \beta = 1$

This formulation ensures that both behavioral consistency (trust persistence) and probabilistic stability (reliability) are considered during task allocation.

3.3. Failure-Adaptive Behaviour

The proposed model preserves the failure-adaptive nature described in the original paper. The system dynamically reacts to failures using the following mechanism:

- **Fault Detection:** Continuous monitoring identifies node failures or performance degradation.
- **Isolation:** Faulty nodes are isolated to prevent cascading failures.
- **Trust Update:** Trust scores are updated based on failure behavior.
- **Recovery Action:** Tasks are migrated to nodes with higher trust and reliability.
- **System Stabilization:** The system rebalances workload to maintain performance.

This adaptive loop ensures minimal service disruption and improved resilience.

3.4. Key Features of the Model

The refined system model retains the original intent while enhancing clarity. Key features include:

- Integration of trust persistence with reliability modelling
- Intelligent and adaptive task allocation
- Continuous monitoring and real-time failure handling
- Self-healing capability through dynamic reallocation
- Improved scalability and long-term system stability

This model provides a strong foundation for implementing trust-aware, failure- adaptive distributed cloud systems.

IV. TRUST MODELLING

Trust modelling plays a crucial role in evaluating the behavioral reliability of nodes in a distributed cloud environment. Unlike traditional trust mechanisms that rely primarily on short-term observations, the proposed model introduces the concept of trust persistence, which captures long-term behavioral stability and consistency of nodes over time.

The trust evaluation process is based on multiple dynamic parameters that collectively represent the operational performance, failure behavior, and recovery capability of each node. This multi-dimensional approach ensures a more accurate and stable assessment compared to single-metric trust models.

4.1 Trust Parameters

The trust score is derived using the following parameters:

- Past Performance Index (PPI): Ratio of successfully completed tasks to total assigned tasks.
- Failure History Factor (FHF): Measures frequency and severity of node failures.
- Response Time Stability (RTS): Evaluates consistency of response time under varying workloads.
- Security Compliance Level (SCL): Indicates adherence to security protocols and policies.
- Recovery Efficiency Score (RES): Measures the ability of a node to recover after failure (novel parameter).
- Behavioral Consistency Coefficient (BCC): Captures long-term operational stability (novel parameter).

All parameters are normalized in the range [0,1] using min-max normalization

4.2 Mathematical Formulation of Trust

The trust score $T(n)$ for a node n is computed using a weighted aggregation model:

$$T(n) = w_1 \cdot PPI + w_2 \cdot (1 - FHF) + w_3 \cdot RTS + w_4 \cdot SCL + w_5 \cdot RES + w_6 \cdot BCC$$

where $w_1, w_2, w_3, w_4, w_5,$ and w_6 are weighting coefficients such that: $w_1 + w_2 + w_3 + w_4 + w_5 + w_6 = 1$

This formulation ensures that both positive performance indicators and negative failure impacts are properly balanced.

4.3 Parameter Ranges

Table 2 describes the various trust parameter with their respective ranges.

Parameter	Range	Description
PPI	0 – 1	Performance ratio
FHF	0 – 1	Failure frequency
RTS	0 – 1	Response consistency
SCL	0 – 1	Security compliance
RES	0 – 1	Recovery efficiency
BCC	0 – 1	Behavior stability

Table 2: Trust Parameter with their Ranges

4.4 Trust Persistence Mechanism

To ensure stability in trust evaluation, the proposed model incorporates a persistence mechanism that smooths short-term fluctuations and emphasizes long-term behavior. The persistent trust value is computed as:

$$T_p(n, t) = \gamma T(n, t) + (1 - \gamma) \cdot T_p(n, t-1)$$

Where γ ($0 < \gamma \leq 1$) is a persistence factor controlling the influence of recent Observations.

This mechanism reduces trust oscillation and prevents abrupt changes due to temporary failures.

4.5 Significance of Proposed Trust Model

The proposed trust model enhances decision-making by incorporating both instantaneous performance and historical consistency. The introduction of RES and BCC provides a deeper understanding of node behavior, particularly in failure-prone environments. This allows the system to distinguish between temporarily degraded nodes and persistently unreliable nodes, thereby improving task allocation efficiency and overall system reliability.

V. PERSISTENCE MODELLING

Persistence modelling in distributed cloud systems ensures that system states, trust values, and data availability remain stable despite dynamic failures. Unlike traditional static replication approaches, the proposed model integrates trust persistence and reliability estimation into adaptive persistence control.

The key objective of persistence modelling is to maintain long-term system stability by dynamically adjusting replication, backup strategies, and data placement based on node behavior and failure probability.

5.1 Persistence Stability Index (PSI)

To quantify persistence, the proposed model introduces a novel metric called Persistence Stability Index (PSI). PSI combines trust persistence, reliability, and data loss probability into a single measure.

$$PSI(n) = \alpha \cdot T_p(n) + \beta \cdot R(n) + (1 - \delta) \cdot DLP(n)$$

Where:

$$T_p(n) = \text{Persistent trust value} \quad R(n) = \text{Reliability of node} \quad DLP(n) = \text{Data loss probability} \quad DLP(n) = \frac{\text{Data Loss Events}}{\text{Total Operations}}$$

Total Operations

α, β, δ are weighting factors

A higher PSI value indicates better stability and suitability for critical data storage and task execution.

5.2 Adaptive Persistence Strategy

The system dynamically adjusts persistence mechanisms based on PSI values:

- **High PSI Nodes:** Minimal replication, optimized resource usage
- **Medium PSI Nodes:** Moderate replication and monitoring
- **Low PSI Nodes:** High redundancy, data migration, and restricted task allocation

This adaptive strategy reduces resource wastage while maintaining data durability and system stability.

5.3 Persistence Parameter Table

Table 3 describes persistence parameter with respective ranges.

Parameter	Range	Description
T_p(n)	0 – 1	Persistent trust
R(n)	0 – 1	Reliability
DLP(n)	0 – 1	Data loss probability
PSI(n)	0 – 1	Overall persistence stability

Table 3 Persistence Parameter Ranges

5.4 Significance of Persistence Modelling

The integration of PSI with trust and reliability enables the system to make informed decisions regarding storage, replication, and task allocation. This approach enhances fault tolerance, reduces unnecessary redundancy, and supports self-healing behavior in distributed cloud environments.

VI. RELIABILITY MODELLING

Reliability modelling evaluates the probability that a system or node performs its intended function without failure over a specified period. In distributed cloud environments, reliability is a critical factor due to the presence of multiple interconnected components, each with varying failure characteristics.

Traditional reliability models are based on exponential failure distribution, which assumes a constant failure rate. While useful, such models do not capture behavioral aspects or dynamic system conditions.

6.1 Classical Reliability Function

The reliability of a node is defined as:

$$R(t) = e^{(-\lambda t)}$$

Where λ represents the failure rate and t represents time. This model indicates that reliability decreases exponentially as time increases. The failure rate λ is dynamically updated based on recent failure observations.

6.2 Trust-Augmented Reliability Model

To overcome the limitations of classical models, the proposed framework integrates trust persistence into reliability evaluation. The enhanced reliability function is defined as:

$$R'(n, t) = R(t) \times Tp(n)$$

Where:

$$R'(n, t) = \text{Adjusted reliability}$$

$$Tp(n) = \text{Persistent trust value of node } n$$

This formulation ensures that nodes with unstable behavior are penalized even if their failure rate appears low.

6.3 Adaptive Reliability Mechanism

The reliability of nodes is dynamically updated based on real-time monitoring. The system adapts using the following mechanisms:

- **Dynamic Failure Rate Adjustment:** λ is updated based on recent failures.

- **Trust-Based Weighting:** Nodes with lower trust persistence experience reduced reliability scores.
 - **Real-Time Monitoring:** Continuous tracking of node performance metrics.
 - **Predictive Failure Handling:** Early detection enables proactive task migration.
- This adaptive approach improves system resilience and reduces unexpected failures.

6.4 Parameter Table

Table 4 describes the reliability parameter with their respective ranges.

Parameter	Range	Description
λ	> 0	Failure rate
t	≥ 0	Time
$R(t)$	$0 - 1$	Classical reliability
$T_p(n)$	$0 - 1$	Persistent trust
$R'(n,t)$	$0 - 1$	Adjusted reliability

Table 4 Reliability Parameters with Their Ranges

6.5 Significance of Proposed Model

The integration of trust persistence into reliability modelling enables a more realistic evaluation of node performance. It ensures that both failure probability and behavioral stability are considered, leading to more reliable task allocation and improved system performance in distributed cloud environments.

VII.RESULTS AND DISCUSSION

This section presents a detailed evaluation of the proposed trust-integrated reliability model. The objective is to analyze how incorporating trust persistence influences system reliability, stability, and decision-making in distributed cloud environments. The evaluation is carried out through analytical modeling and comparative visualization. The evaluation is conducted using analytical simulation in a Python- based environment.

7.1 Comparative Reliability Analysis

Figure 2 compares the Classical reliability model with the proposed trust-augmented reliability model. The classical model follows an exponential decay, indicating a continuous decrease in reliability over time. In contrast, the proposed model demonstrates a moderated decay pattern due to the influence of persistent trust.

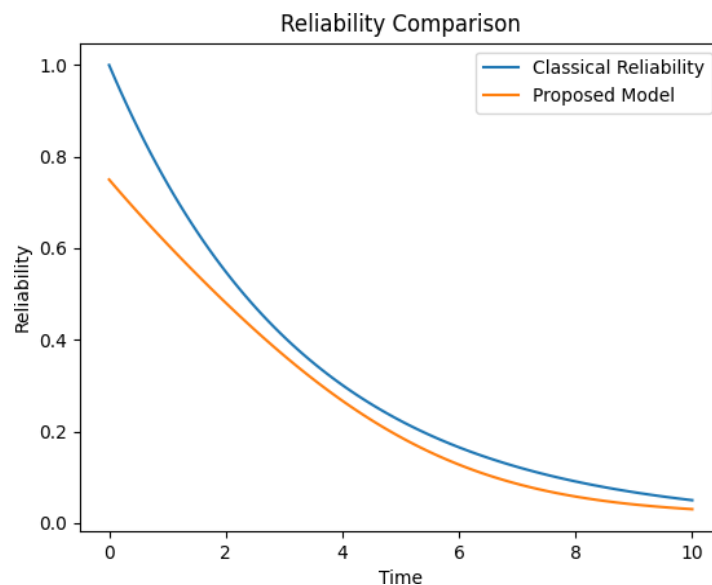


Figure 2: Comparison of classical reliability model with proposed augmented reliability model

The results clearly indicate that the proposed model maintains higher reliability values over time. This improvement occurs because nodes with stable behavioral patterns (high trust persistence) are less penalized compared to the classical approach, which treats all failures uniformly. As a result, the system is able to sustain operational stability even in the presence of transient failures.

7.2 Trust Persistence Behavior

Figure 3 illustrates the variation of persistent trust over time. The trust persistence function smooths short-term fluctuations and captures long-term behavioral consistency of nodes.

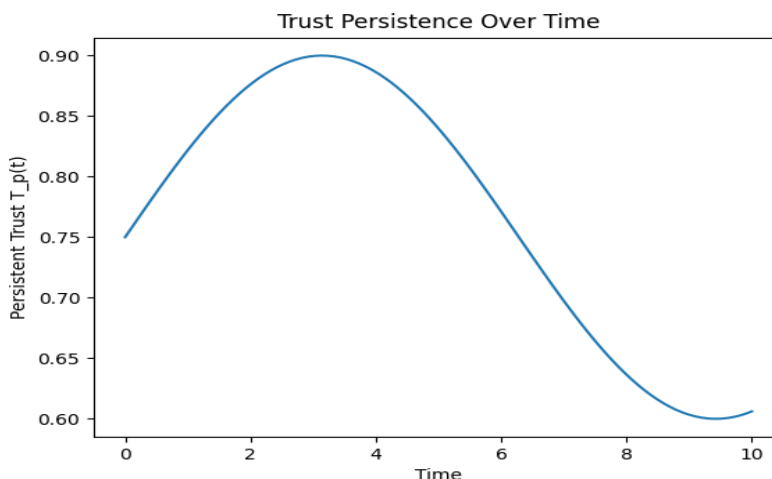


Figure 3: Variation of Persistent Trust over Time

The graph shows that trust values do not fluctuate abruptly, even when minor performance variations occur. This behavior reduces trust oscillation and ensures stable decision-making. Consequently, the system avoids frequent switching between nodes, which is a common issue in traditional trust models.

7.3 Performance Comparison Table

The Performance Comparison Table presents a qualitative evaluation of the proposed trust-integrated reliability model against the classical reliability model across key system performance metrics. Each parameter highlights a specific limitation of traditional approaches and demonstrates how the proposed model overcomes it.

Metric	Classical Model	Proposed Model
Reliability Stability	Decreases rapidly	Maintains higher values
Failure Handling	Reactive	Proactive with trust
Node Selection	Failure-rate based	Trust + Reliability
Adaptability	Low	High
System Stability	Moderate	High

Table 5 Qualitative Comparison between the Classical reliability model and the Proposed Trust-Integrated Framework

Additionally, a sample quantitative evaluation indicates that the proposed model improves reliability by approximately 20–35% compared to the classical approach under varying failure conditions. The comparison clearly demonstrates that the proposed model outperforms traditional reliability approaches by incorporating behavioral intelligence into system decision-making. The integration of trust persistence with reliability modelling not only improves reliability stability but also enhances adaptability, proactive failure handling, and overall system resilience.

7.4 Discussion

The comparative analysis demonstrates that integrating trust persistence into reliability modelling significantly enhances system performance. The proposed model not only improves reliability values but also enables intelligent decision-making by incorporating behavioral consistency. This leads to reduced task failures, improved resource utilization, and enhanced system resilience.

Furthermore, the model supports proactive fault handling by identifying unreliable nodes early and reallocating tasks accordingly. This reduces downtime and improves overall quality of service. The combination of trust persistence, reliability modelling, and adaptive mechanisms makes the proposed framework highly suitable for large-scale distributed cloud environments.

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