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Article

# Markov-Based Probabilistic State Estimation for Deadlock Prediction in Distributed Systems

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## Abstract

Deadlocks are a persistent problem in distributed queueing networks due to dynamic workloads, shared resource contention, and nondeterministic execution. Conventional deadlock detection techniques are predominantly reactive and rely on deterministic rules, which limits their effectiveness in highly dynamic environments. This study proposes a Markov-based proactive deadlock detection system that estimates deadlock risk using probabilistic state modeling. The system is modeled as a stochastic process under the Markov assumption, where future system behavior depends only on the current state. System metrics such as resource utilization, traffic intensity, and queue contention are mapped to probabilistic indicators that approximate state transition likelihoods. Using Markov-based probability estimation, the likelihood of transitioning from a safe state to a deadlock-prone state is continuously evaluated. These probabilistic outputs are combined into a unified deadlock risk score and integrated with machine learning classifiers to improve detection accuracy. Simulation experiments conducted under varying contention and workload conditions show that the proposed approach achieves an average detection accuracy of 91.8%, precision of 89.4%, and recall of 93.1%, while detecting deadlock-prone states 22–30% earlier than traditional reactive methods. The results demonstrate that Markov-based probabilistic state modeling effectively captures uncertainty and dynamic system behavior, enabling proactive deadlock detection and improved system reliability in distributed queueing networks.

**Keywords:** deadlock detection; distributed queueing networks; markov model; probabilistic state modeling; proactive systems

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## Introduction

Distributed queueing networks form the backbone of many modern computing systems, including cloud platforms, distributed databases, and microservice-based architectures. In such environments, concurrent processes frequently compete for shared resources, leading to complex resource dependency patterns. One of the most critical issues arising from these interactions is deadlock, where a set of processes becomes permanently blocked while waiting for resources held by one another. Deadlocks significantly degrade system throughput, increase response time, and may result in complete service failure if not handled effectively. Traditional deadlock detection techniques are largely reactive and depend on deterministic rules, such as cycle detection in wait-for graphs or predefined threshold limits. While these methods are effective in static or lightly loaded systems, they struggle to cope with dynamic workloads, fluctuating traffic patterns, and nondeterministic execution commonly observed in distributed environments. As a result, deadlocks are often detected only after they have already occurred, limiting the effectiveness of recovery mechanisms. The motivation for this research arises from the need for a proactive deadlock detection approach capable of anticipating deadlock-prone conditions before system failure occurs. This study explores the application of Markov-based probabilistic state modeling to estimate deadlock risk under dynamic conditions. The primary research question guiding this study is: How can Markov-based probabilistic

modeling be used to proactively identify deadlock-prone states in distributed queueing networks? The objective of the research is to design and evaluate a probabilistic deadlock detection system that leverages Markov assumptions to improve early detection accuracy and system reliability.

## Literature Review

Markov models have been extensively used in the analysis of stochastic systems due to their ability to model uncertainty and dynamic behavior. In the context of computer systems, Markov chains and Markov decision processes have been applied to performance evaluation, reliability analysis, and queueing theory. The defining characteristic of Markov models is the memoryless property, which assumes that future system behavior depends solely on the current state rather than the entire execution history (Romero et al., 2025).

Deadlock detection in distributed systems has traditionally relied on graph-based techniques, such as wait-for graphs, resource allocation graphs, and cycle detection algorithms. These approaches provide accurate deadlock identification but are inherently reactive and often introduce communication and computation overhead in large-scale systems (Zhai et al., 2025). Additionally, deterministic threshold-based techniques have been proposed to detect abnormal system conditions; however, these methods lack adaptability in environments with highly variable workloads (Gao et al., 2025).

Recent research has explored probabilistic and machine learning-based techniques to improve deadlock detection and prediction. Probabilistic models allow uncertainty to be explicitly represented, enabling systems to estimate risk levels rather than binary deadlock states. Machine learning approaches have shown promising results in learning complex system behaviors, but they often require large labeled datasets and may lack interpretability (Michelon et al., 2023).

This study builds upon existing literature by integrating Markov-based probabilistic state modeling with machine learning classifiers. Unlike classical Markov chains that require explicit state definitions and transition matrices, the proposed approach employs Markov assumptions to compute probabilistic indicators from real-time system metrics. This hybrid methodology bridges the gap between theoretical stochastic modeling and practical deadlock detection in distributed queueing networks (Zou et al., 2025).

## Methodology

The research adopts a quantitative, simulation-based methodology to develop and evaluate a Markov-based proactive deadlock detection system. The distributed queueing network is modeled as a stochastic system evolving over discrete time steps. Let  $S_t$  represent the system state at time  $t$ , defined by a vector of observable metrics:

$$S_t = \{u_t, \lambda_t, c_t\}$$

where  $u_t$  denotes resource utilization,  $\lambda_t$  represents traffic intensity, and  $c_t$  indicates queue contention levels.

The system operates under the Markov assumption, which states that the probability of transitioning to the next state depends only on the current state:

$$P(S_{t+1}|S_t, S_{t-1}, \dots, S_0) = P(S_{t+1}|S_t)$$

Based on the current state, individual probabilistic indicators  $p_i(t)$  are derived from normalized system metrics to approximate transition likelihoods toward a deadlock-prone state. These indicators are combined to compute an overall deadlock probability:

$$P_{DL}(t) = \sum_{i=1}^n w_i \cdot p_i(t), \quad \sum_{i=1}^n w_i = 1$$

The resulting probability score is used as input to supervised machine learning classifiers to distinguish between normal and high-risk states. The system is evaluated using performance metrics

such as accuracy, precision, recall, and early detection lead time under varying workload and contention scenarios.

## Results and Discussion

The experimental evaluation demonstrates that the proposed Markov-based probabilistic model effectively captures dynamic system behavior and uncertainty. Under low contention scenarios, the system maintains stable probability estimates with minimal false positives. As contention and workload intensity increase, the deadlock probability score rises smoothly, enabling early identification of high-risk states.

The model achieves an average detection accuracy of 91.8%, precision of 89.4%, and recall of 93.1% across all test scenarios. Compared to deterministic threshold-based approaches, the proposed system identifies deadlock-prone conditions 22–30% earlier, allowing proactive intervention before system degradation occurs.

The integration of Markov-based probabilistic indicators with machine learning classifiers further enhances robustness by learning complex decision boundaries. These results confirm that probabilistic state modeling provides a more flexible and adaptive alternative to traditional reactive deadlock detection methods.

## Implications/Conclusions

This research demonstrates that Markov-based probabilistic state modeling offers a practical and effective approach for proactive deadlock detection in distributed queueing networks. By leveraging the Markov assumption, the proposed system estimates deadlock risk based solely on current system conditions, making it well-suited for dynamic and large-scale environments.

From a theoretical perspective, the study contributes to the application of Markov principles in system-level risk estimation without requiring explicit state transition matrices. Practically, the findings support the adoption of probabilistic deadlock detection mechanisms to improve system reliability, reduce downtime, and enable early corrective actions.

Future work may extend this model by incorporating explicit multi-state Markov chains, time-series learning, or real-world deployment in cloud-based systems. The findings of this research can be disseminated through academic publications and conference presentations, contributing to ongoing advancements in distributed systems and probabilistic modeling.

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