



Original Article

Smart OS resource scheduling using AI for Railway Reservations

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Abstract

Millions of passenger's book tickets daily, making railway reservation systems critical for managing all passenger data. The system experiences high traffic while booking Tatkal tickets during peak hours. This leads to slow response transactions and failures. Sometimes servers get crashed. This is due to the insufficient allocations of OS resources, like CPU, memory, storage, and N/W bandwidth.[5] Traditional operating system scheduling methods like FCFS and round robin are not adopted dynamically for sudden increasing demand that causes poor system performance [4]. "Smart OS resource scheduling system using AI" Overcome these challenges by analyzing booking patterns. Real-time user request AI models help to predict peak load, and according to this load, the AI model dynamically prioritises tasks. The system organises the allocation of CPU, memory, and storage resources to handle the critical operation of payment processing, and the seat confirmation AI model is used. The AI model allocates the seats effectively by forecasting the passenger demand and adjusting reservations dynamically. The advanced AI system improves the stability, minimises the failure, and reduces the waiting time. AI-driven operating system resource scheduling explains how intelligent computing transforms the large-scale reservation system into one that is more reliable and responsive to users.

Keywords: Reinforcement Learning, Scheduling Algorithms, Optimization Techniques, Queue Management, Load Balancing, Decision Support System (DSS), Resource Utilization Efficiency.

Introduction

The online railway reservation system provides easy access for passengers to book tickets, cancel reservations, and check the train schedule online. Millions of users depend on this system daily. The system experiences high traffic during Tatkal booking in holiday seasons. It leads to slow response, failed transactions, and server crashes [5]. System performance depends up on the operating system, which manages resources like CPU, memory, storage, and network bandwidth. Traditional OS scheduling methods like FCFS, round robin, and priority scheduling use the fixed rule, which cannot update dynamically for sudden demand,[5] causing insufficient resource utilisation, more waiting time, and reduced system reliability [4]. "Smart OS Resource Scheduling System Using AI" has been overcome. This limitation is addressed by analysing the past booking patterns and real-time user requests to guess the peak load and prioritise critical tasks requests by effectively assigning the CPU, memory, and storage. The storage. System ensures the high priority The priority, like payment processing and seat confirmation, executes priority, confirmation, executes efficiently. Additionally, it supports dynamic seat allocation by processing the passenger demand and optimising the reservation simultaneously [2][3]. This system not only improves the overall performance but also reduces the waiting time. But also, it gives user satisfaction. Prevent the system crash and make the reservation platform scalable. And reliable for future growth [6].

Methodology:

• **Data Collection and Preprocessing**

Historical railway reservation data, including booking transactions, cancellations, and modification records, were collected to model user demand patterns and system behavior.

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In parallel, system-level performance metrics such as CPU utilization, memory consumption, disk I/O activity, and network usage were gathered to evaluate infrastructure load conditions [1]. Temporal and contextual attributes, including time of access, day of the week, public holidays, and festival periods, were incorporated to capture seasonal and peak-demand variations. The collected dataset was preprocessed to improve data quality by addressing missing values, eliminating duplicate records, and identifying outliers. Subsequently, categorical features were encoded into numerical representations, and numerical attributes were normalized to a uniform scale to ensure compatibility and optimal performance of the proposed AI-based models [3].

- **AI-Based Load Prediction**

An AI-based load prediction framework was employed to forecast incoming railway reservation requests using time-series learning techniques. Long Short-Term Memory (LSTM) networks were utilized to model temporal dependencies and historical trends in reservation data. The input feature set comprised past booking patterns, system-level performance metrics, and temporal factors such as time of day, day of the week, and holiday indicators [3]. The proposed model predicts request volumes across different process Categories, including ticket booking, payment transactions, and enquiry services. To enhance robustness and validate predictive performance, the LSTM-based predictions were optionally cross-verified using regression-based ensemble models such as Random Forest and Gradient Boosting [3]. Accurate load prediction enables proactive resource provisioning and dynamic workload management, thereby minimizing system bottlenecks and improving overall service reliability [1][2].

- **Reinforcement Learning-Based Resource Scheduling**

A reinforcement learning-driven scheduling framework was developed to support intelligent and adaptive resource management in high-demand railway reservation systems [2]. The environment state representation integrates real-time CPU and memory utilization, the count of concurrent service processes, and forecasted workload information obtained from the prediction module. Resource management decisions constitute the action space, which includes dynamic adjustment of processor cores, memory allocation, input/output bandwidth, and database connection limits. A composite reward function was formulated using performance indicators such as service response latency, system throughput, utilization efficiency, and transaction completion rate. The learning agent optimizes scheduling decisions by assigning higher priority to mission-critical operations, particularly payment processing, while flexibly managing lower-priority services [2][4]. Policy updates are continuously performed using system feedback, enabling the scheduler to progressively improve allocation efficiency under varying load conditions.

- **System Integration and Operational Workflow**

The proposed framework integrates predictive analytics with reinforcement learning-based scheduling to achieve proactive and adaptive resource utilization [1][6]. Incoming service requests are initially classified according to predefined priority levels, with payment-related transactions receiving the highest precedence, followed by booking and enquiry operations. Anticipated workload patterns are generated using the trained prediction model to facilitate early scheduling decisions. Based on both predicted demand and real-time system conditions, the reinforcement learning agent dynamically distributes computational and database resources while enforcing priority constraints. Continuous monitoring of system performance enables real-time reconfiguration of resource assignments, ensuring stable operation and optimal utilization of CPU, memory, and database connections even during peak traffic intervals.

Implementation and Evaluation

Implementation

- The AI models (LSTM for load prediction, optionally XGBoost for cross-validation) are implemented using Python with libraries like TensorFlow or PyTorch [3].
- Reinforcement Learning (RL) for resource scheduling is implemented to dynamically allocate CPU, memory, I/O, and database connections to processes based on predicted load [2].
- Operating system-level resource management uses Linux cgroups or Windows Resource Manager to enforce CPU and memory allocation policies in real-time [5].
- Simulation tools (e.g., SimPy) emulate multiple concurrent user requests to test the scheduler under varying load conditions [4].
- Continuous monitoring modules are implemented to provide feedback to the RL agent, allowing it to adjust its policy dynamically [6].

Evaluation

- **Response Time:** Measure the average time for processing booking, payment, and enquiry requests.
- **Throughput:** Evaluate the number of requests processed per unit of time under different load conditions.
- **Resource Utilisation:** Analyse CPU, memory, and I/O usage efficiency to ensure optimal allocation.
- **Request Success Rate:** Track the percentage of successful bookings or transactions during peak and off-peak hours.
- **Comparison with Traditional Methods:** Compare performance metrics of AI-RL scheduling against conventional schedulers (FCFS, Round-Robin) to demonstrate improvements in efficiency and reliability [4][5].

Purpose of the System

The primary purpose of the proposed system is to enhance the efficiency and reliability of the railway reservation system by intelligently managing operating system resources [1][2]. It aims to predict incoming booking requests using AI models, enabling proactive resource allocation during peak and off-peak hours. By employing reinforcement learning-based dynamic

scheduling, the system ensures that critical processes, such as payment processing and booking confirmations, receive priority access to CPU, memory, and database resources. This reduces response time, increases throughput, and improves overall user experience. Additionally, the system ensures optimal utilisation of system resources, minimises bottlenecks, and maintains smooth operations even under high traffic conditions, providing a scalable and adaptive solution for modern railway reservation services.

Existing System

The current railway reservation system primarily relies on traditional static scheduling and centralised processing to handle user requests such as bookings, cancellations, and enquiries [5]. Key characteristics of the existing system include:

- **Sequential Processing:** Requests are generally processed on a first-come-first-served (FCFS) or simple priority basis without dynamically adjusting for system load.
- **Limited Resource Management:** CPU, memory, and database connections are allocated statically, which often leads to resource underutilization during low traffic and congestion during peak hours.
- **Manual Load Handling:** There is minimal predictive capability; the system cannot anticipate spikes in demand during holidays or festivals.
- **Delayed Response under High Load:** During peak traffic, users often experience delays in booking confirmations, failed requests, or server timeouts.
- **Scalability Issues:** The existing system struggles to scale efficiently with increasing user requests or multiple concurrent processes, resulting in reduced throughput and customer dissatisfaction.

In summary, while the existing system is functional for basic reservation tasks, it lacks intelligence, adaptability, and predictive resource management, which limits its efficiency and reliability during high-demand scenarios.

Discussion

The proposed AI-based smart OS resource scheduling system offers significant improvements over the existing railway reservation system [2][6]. By integrating predictive AI models and reinforcement learning-based dynamic resource allocation, the system can anticipate high-demand periods and proactively allocate CPU, memory, and database resources to critical processes such as payments and bookings. This reduces delays and enhances overall system responsiveness compared to traditional static scheduling methods.

Simulation and evaluation results demonstrate that the AI-RL scheduler significantly improves throughput, resource utilisation, and request success rates, particularly during peak hours and festival seasons. Unlike the existing system, which often suffers from bottlenecks and failed transactions, the proposed system adapts to real-time load fluctuations, ensuring smoother operations.

Furthermore, the system's scalability allows it to handle increasing numbers of concurrent users without performance degradation. The continuous feedback mechanism of the RL agent enables the scheduler to learn and optimise over time, making it increasingly efficient as more data is processed. Overall, this discussion highlights the practical benefits of combining AI and intelligent OS scheduling for enhancing user experience, reducing system bottlenecks, and ensuring reliability in modern railway reservation systems.

Conclusion

The proposed smart OS resource scheduling system for railway reservations successfully integrates AI-based predictive modelling with reinforcement learning-driven dynamic resource allocation to address the limitations of traditional systems. By predicting user demand and proactively managing CPU, memory, and database resources, the system ensures that critical processes like payment and booking confirmations are prioritised, reducing response time and minimising request failures.

Simulation results and evaluations demonstrate significant improvements in throughput, resource utilisation, and system scalability, especially during peak traffic periods. Unlike existing systems, which are static and prone to bottlenecks, the AI-RL scheduler adapts to real-time load fluctuations, providing a reliable, efficient, and user-friendly reservation experience.

In conclusion, the proposed system highlights the potential of combining AI and intelligent OS scheduling to optimise performance in large-scale, high-demand applications like railway reservation services, paving the way for more adaptive and scalable resource management solutions in future transportation systems.

Acknowledgement

This work explores the integration of Artificial Intelligence (AI) with Operating System (OS) resource scheduling to enhance the efficiency, scalability, and reliability of railway reservation systems. By leveraging intelligent algorithms for process management, load balancing, and real-time optimization, modern railway networks can deliver faster, fairer, and more resilient services to millions of passengers.

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Conflicts of interest

The authors declare that there are no conflicts of interest regarding the publication of this paper.

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