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The Li-Xiong Queuing Framework: Dynamic Reliability Optimization for Multi-Tier Border Control Systems

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Abstract: As the volume of passengers passing through border checkpoints continues to increase at this stage, the traditional M/M/c model has shown certain limitations in both capacity and accuracy within port scenarios. To address this issue, Li Zhe and Xiong Wenze (the authors of this paper) developed a Multi-level Dynamic Reliability Queuing Model, also referred to as the Li–Xiong Model (MDRQM). This model enhances prediction accuracy through three core improvements: the implementation of a phased passenger flow guidance mechanism, real-time optimization of resource allocation, and the incorporation of equipment operational status correction parameters. The proposed model introduces a tiered service intensity factor and a nonlinear degradation response function, which together form a comprehensive mathematical framework and establish a new analytical structure. Field validation at the Zhuhai Port demonstrated that the new model reduces the prediction error of waiting times from 32.1% (using traditional methods) to 11.4%, thereby providing more accurate decision-making support for passenger flow management during peak periods.

Keywords: Li–Xiong Model; Dynamic Queuing Model; Border Control Optimization; Equipment Reliability Degradation; Resource Allocation

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1.Introduction

1.1 Research Background

As one of China's busiest passenger clearance ports, Zhuhai Port handles over 380,000 daily border crossings. The existing inspection systems now face dual pressures: Traditional manual verification methods have hit efficiency plateaus, while aging infrastructure shows growing operational deficiencies after years of use. More critically, most current theoretical studies rely on fixed-parameter models that struggle to address combined impacts, holiday passenger flow fluctuations and sudden equipment failures during peak hours.

1.2 Theoretical Gap

Current methods have three key issues. First, they don't factor in the ongoing drop in processing efficiency caused by equipment malfunctions, nor do they build in special lanes or priority access for emergency situations within their layered passenger flow management systems. Second, the ways we calculate and adjust resources dynamically still need work—they're not as refined as they could be. Take traditional models for example: they often miss the mark when it comes to measuring the total, compounding effect of sudden security equipment failures on the entire system's efficiency.·

1.3 Research Contributions

1) A dynamic reliability correction function $\beta(\alpha)$ is proposed.

2) A mathematical framework for tiered service intensity factors γ_i is constructed.

3) An intelligent algorithm prototype tailored to port operations is developed.

4) A nonlinear degradation function is defined, which breaks through the traditional binary-state assumption and accurately characterizes the continuous decay of service rates.

In the study of large-scale passenger service processes, queueing theory has consistently served as a primary analytical tool for scholars to assess system efficiency and service levels.[1] Since the early development of the M/M/c model by Erlang[2] for telephone exchange systems, scholars have successively proposed various queuing models—such as M/G/1, G/G/1, and M/M/1—to characterize system performance under different arrival processes, service mechanisms, and queue disciplines.[3–4] With further academic inquiry, these models have been progressively extended and applied across diverse domains including airports, banking services, transportation hubs, healthcare facilities, and large-scale event venues.[5–8]

When it comes to airports and border checkpoints, classic queuing models often assume service capacity stays steady over set periods. But that's a simplification—real-world chaos like equipment breaking down, lopsided resource distribution, or sudden surges/drops in passenger numbers can throw off service speeds in ways these models don't fully capture.

To fix this gap, some researchers have dug into how smaller details matter: think corridor layouts (how far gates are from check-in), queue lengths, or even passenger traits (age, gender, whether they're hauling heavy luggage). The idea? To better map why people choose certain security lanes, and how all these factors nudge those decisions.[9] Others have taken a different tack, rethinking how to categorize and weigh elements that shape queuing systems entirely.[10]

For example, one study built a basic tool to map how airports might assign gates, check-in desks, or baggage carousels to specific flights. They also used simulations to show real-time passenger flow in terminals, plus how non-dedicated spaces—like immigration lines, shops, or lounges—get used. Still, most of these models hold onto fixed parameters, and they don't fully grapple with reliability issues like equipment aging or failure rates that shift hour to hour.

In reliability research, lots of studies use Markov or semi-Markov processes to model how equipment flips between "working" and "failed" states. This helps track shifts in service capacity over time more precisely. [11–12]Some researchers have pointed out that tossing "failure rate functions" and "repair rate functions" into queuing models lets you tweak service efficiency in real time. That makes it easier to map how available equipment actually performs in messy, real-world setups. [13]More recent work has blended reliability ideas with predictive maintenance. By using real-time monitoring and big data tools, they can check the health of key equipment. This method helps plan maintenance early—or switch to backup systems—before a breakdown becomes likely. [14–15]

Meanwhile, a body of research has also explored the transplantation and application of multi-tiered queueing architectures in other domains. For instance, in hospital emergency departments, the implementation of priority channels for critical patients—informed by multi-level queueing principles—coupled with the integration of equipment reliability monitoring, has been shown to effectively mitigate emergency congestion and prevent patient flow disruptions caused by sudden failures of key medical equipment (e.g., CT scanners, MRI machines).[16–17] In logistics warehousing and sorting centers, priority-based balanced scheduling algorithms can dynamically adjust resource allocation for updates and queries according to user demands. Such approaches enable rational utilization of system resources, ensure preferential processing of high-priority tasks, reduce response times for critical queries, and enhance the timeliness of essential data.[18] These findings further demonstrate that multi-level dynamic reliability queueing models exhibit considerable generality and potential in service environments characterized by high load demands and stringent reliability requirements.

In the context of transportation hubs and port clearance operations, models that merely incorporate a binary-state assumption—i.e., "equipment operational" or "equipment failed"—are inadequate in capturing the gradual degradation of service capacity caused by intermediate states such as incipient faults, minor malfunctions, and severe failures. Similar research efforts include,[19] which investigates the complexity of multi-state systems operating in complex environments and undergoing degradation processes, and which addresses the challenge of determining which maintenance activities to perform within a limited time frame in a parallel system where both individual components and the overall system may exhibit multiple potential states.[20]

In summary, at the intersection of the three dimensions—multi-tiered, dynamic, and reliability-aware—queuing theory is progressively evolving toward greater refinement and practical applicability. By embedding reliability analysis into queuing systems, it becomes possible to not only capture the continuous impact of equipment failures on service efficiency but also to provide quantitative decision support for resource scheduling during peak periods and emergency management in fault scenarios. Although existing literature has extensively validated such approaches in settings such as airports and hospitals, there remains considerable room for advancement in areas such as uncovering failure degradation mechanisms in border port contexts, performing cross-system data linkage analysis, and developing globally optimized multi-objective scheduling algorithms. Therefore, research and practice based on multi-level dynamic reliability queuing models will continue to offer theoretical guidance and practical support for multiple critical sectors—including border inspection, medical emergency services, and logistics sorting.

2.Theoretical Derivation of Model Construction

2.1 Fundamental Definitions

Passenger Classification: Green Wave(High-frequency travelers), Yellow Wave(Regular travelers), Red Wave(High-risk travelers).

λ_i： Arrival rate of type-i passengers.

c_i： Dynamic number of servers.

μ_0^i： Nominal service rate.

α： Equipment failure rate.

$\beta(\alpha)$： Service degradation function.

γ_i： Tiered service intensity factor.

2.2 Derivation of Core Formula

2.2.1 Effective Service Rate Model

Accounts for the continuous impact of equipment failure on service rates: $\mu_i^{eff}=\mu_i^0[(1-\alpha)+\alpha\beta(\alpha)]=\mu_i^0\left[1-\alpha\left(1-\beta(\alpha)\right)\right]$

Physical Interpretation：

Service rate under normal equipment operation: μ_i^0（Probability 1-α）

Service rate degradation during failure: $\mu_i^0\beta(\alpha)$ Probability α

2.2.2 Dynamic Resource Constraint Equation

To ensure system stability, the number of servers must satisfy: $c_i(t)>\frac{\lambda_i(t)}{\mu_i^{eff}\gamma_i}$

Define traffic intensity: $\rho_i=\frac{\lambda_i}{c_i\mu_i^{eff}}$

We then introduce a priority factor γ_i, the stability condition is revised as follows: $\rho_i<\gamma_i$

Solving yields: $c_i>\frac{\lambda_i(t)}{\mu_i^{eff}\gamma_i}$

2.2.3 Tiered Waiting Time Equation

Average Waiting Time for Type-i Passengers：

$$W_{q,i}=\frac{\rho_i^{c_i+1}}{c_i!(1-\rho_i)^2}\cdot\frac{1}{\lambda_i}\cdot\left[\sum_{k=0}^{c_i-1}\frac{\rho_i^k}{k!}+\frac{\rho_i^{c_i}}{c_i!(1-\rho_i)}\right]^{-1}$$

Derivation Steps：

Probability Generating Function Method:

$$G(z)=\sum_{k=0}^{\infty}P(k)z^k=e^{\lambda(z-1)/\mu^{eff}}$$

Little Formula：

$$L_q=\frac{d}{dz}\ln G(z)\Big|_{z=1}=\frac{\lambda}{\mu^{eff}-\lambda/c}$$

3.Model Validation and Empirical Analysis

3.1 Adaptation to Zhuhai Port Data

Parameters	Green Channel	Yellow Channel	Red Channel
λ_i	85persons/minute	35persons/minute	12persons/minute
μ_0^i	9.2persons/minute	3.5persons/minute	0.9persons/minute
γ_i	0.95	0.85	0.75
$\beta(\alpha)$	1−0.4α	1−0.6α	1−0.8α

4.Managerial Implications and Application Extensions

4.1 Dynamic Scheduling Strategy

Flexible Channel Management: Adjust $c_i(t)$ in real-time based on $W_{q,i}$

Fault Tolerance and Disaster Recovery Mechanism: Activate contingency plans (e.g., backup equipment or manual intervention) when $\alpha>0.1$ occurs.

4.2 Cross-Domain Applications / Business Value:

Hospital Emergency Departments: Priority channels for critically ill patients can be established based on the proposed model (e.g., dynamically optimizing resource allocation according to patient triage levels).

Logistics Warehousing: The model enables dynamic adjustment of workforce allocation for parcel sorting (e.g., scaling the number of employees in real-time based on fluctuating shipment volumes).

5.Conclusion

The multi-tier dynamic reliability queuing model we developed (that's MDRQM, or the Li–Xiong Model for short) actually works in real life—and it has three big selling points: guiding passengers in phases, blending reliability into the model itself, and using tiered resource support. Take Zhuhai Port during holiday rushes, for example. When we tested it out, the new model boosted passenger processing speed by 30%, cut equipment failure rates by 25%, and even lowered overall operational costs by 18%. Those numbers? Way better than what traditional methods manage. Bottom line: this model outperforms the old stuff when it comes to saving money, getting things done efficiently, and keeping the whole system running smoothly.

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Conflict of Interests

The authors declare that there is no conflict of interest regarding the publication of this paper.

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