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Design of Reliable Queue Systems in Complicated Logistics Networks by Using Mathematical Programming Methods

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ABSTRACT: How to construct strong queuing schemes in a network logistics setting using mathematical programming will be considered in this paper. As global supply chains get increasingly complex, Effective management of queues at logistics hubs is crucial for business performance. This work provides a unifying structure which combines queueing models and mathematical programming methods to minimize waiting time, maximize capacity utilization, and optimizing the allocation of resources (e.g., servers) in an unknown demand environment. We employ both analytical models (e.g. M/M/c queueing systems) and simulation techniques developed by means of WinQSP software to explore performance measures under varying circumstances. For illustration, sortation systems of a realistic distribution center network have been placed in simulated. The computational results also show that our technology can reduce the average waiting time by 42% and increase the system's utilization rate by 28% compared to traditional methods by applying mathematical programming for optimal server scaling. The findings of the study will enable logistics managers to develop stable queuing systems that are responsive to demand fluctuation and service performance. This study bridges the gap between queuing theory and practical logistics applications, providing managers with actionable insights.

Keywords: Mathematical programming, Queueing theory, Logistics networks, Resilient optimization, WinQSP.

1. INTRODUCTION

There is larger and resource-intensive (due to exponential growth in e-commerce and globalization) logistics networks. It is even more so, the better queuing service a business can offer the more competitive it will be [1]. These are intersectional spaces where thousands of people and things stream into and out of every day. This causes congestion and reduces supply chain performance [2]. Traditional heuristic queue control methods are not capable of managing dynamic demand and operational unpredictability in logistics today [3].

Analytic Optimization of Queueing System Design: Analytic optimization of queueing system design can be posed as a mathematical programming problem in a formal axiomatic framework that can trade-off service capacity, waiting costs, and resource constraints in analytically sound ways [4]. The precondition for this benefit is that ad-hoc solutions are replaced by mathematical optimization where the decision maker can identify the best global system settings which not only enhance performance – and keeps the system stable under varying demand patterns and service time variance [5].

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The RQSD is motivated by a queuing system design problem in a network logistics structure with multiple decision levels. It This is not scientifically accurate. It would be better: “It identifies which servers are to be retained, how resources will be allocated to network nodes, what service priorities are assigned, and which queuing rules apply based on the arrival process. To network nodes, what service priority has been assigned, and what is a queueing rule depending on arrival process [6]. Such decisions must balance competing objectives, e.g., minimise customer wait time vs avoid costs getting too high or throughput falling too low and system instability under heavy load [7].

The development of computer science and simulation technology has made the research on queuing systems more sophisticated [8]. Software applications such as WinQSP offer analysts the means to simulate complex queue scenarios and performance measurements, and make decisions based on a variety of configurations prior to implementation [9]. Remains underutilized in logistics applications. [10].

The present study fills an important gap in existing literature by proposing a generic framework that integrates analytical queueing models and linear/mixed-integer programming (LP/MIP) techniques for such complex logistics networks. This paper has made three main contributions: (1) optimization models formulation for multi-server queue design under demand uncertainty, (2) generating of a WinQSP-based simulation methodology to assess the robustness of queue design and (3) empirical verification based on real logistics network data that proves potential usefulness gained by dynamic approach.

Many approximate analytic methods associated with the mathematical programming provide us accurate results which allow us to study behavior of the solution [1,2,3]
Three papers are:

1. An analytic solution for Riccati Matrix delay differential equation using coupled homotopy-Adomian Approach [11].
2. A novelty Multi-Step Associated with Laplace Transform Semi Analytic Technique for Solving Generalized Non-linear Differential Equations [12].
3. An efficient semi analytic technique for solving non-linear initial value problems [13].

This study primarily contributes by integrating stochastic queuing models with mathematical programming techniques, including Mixed-Integer Linear Programming. Traditional models depend on deterministic data; however, the integration of queuing theory enables the system to accommodate dynamic uncertainties such as changeable demand, processing bottlenecks, and inconsistent service times. The mathematical software determines optimal facility placements and capacities, while the queuing component regulates congestion and wait times meticulously.

The remainder of this paper is structured as follows: Section 2 discusses the literature mainly related to applications of queueing theory and mathematical programming in logistics. Then, section 3 gives the details of the research methodology by presenting mathematical models and simulation environment involved. In Section 4, we offer an applied analysis with data on WinQSP software. Section 5 provides results and implications for managers. Section 6 is the concluding section with some suggestions for further research.

2. LITERATURE REVIEW

2.1 QUEUEING THEORY OF LOGISTICS PROCESS NETWORKS

Queueing theory has played fundamental role in analysis and optimization of service systems since work of Erlang on telephone networks [14]. Queueing models are used to characterize the operation of systems which have arrivals (vehicles, containers or orders) waiting in queues -- before receiving a service and eventually leaving [15], [16]. The so-called classical M/M/c-K model, i.e., the case with Poisson arrivals and exponentially distributed service times having c parallel servers, admits tractable analysis for important performance measures like average waiting time, queue length at any instant of time and system utilization [17], [18].

Basic queueing models have been further developed for logistics by recent research. Queueing networks with batch Markovian arrival processes can be used to model railway stations and engineered to provide detailed modeling of hierarchical routing structures [19], [20]. Other applications to port operations, warehouse receiving areas, and cross docking facilities illustrate how queueing analysis can be used to guide capacity planning and resource allocation decisions [21]. Multi-phase queueing system with priority classes is studied for multiple types of shipment to justify different service regimes [22], [23].

The queuing theory and network optimization are combined in order to deal with the interrelations between a plurality of service nodes in complicated logistic systems [24], [25]. Tandem queuing networks are used to capture sequential processing in distribution centers, and network queueing models account for routing flexibility and load balancing opportunities [26], [27]. - Studies on the Blood Donation systems show how queueing theory is used in finding a trade-off between quality of service to donors and efficiency of collection planning [28], [29].

2.2 LOGISTICS NETWORK DESIGN AND QUEUE CONTROL

Queue Node The design of logistic networks must include such queueing events at several levels i.e., suppliers, plant production facilities, distribution centers and customer delivery points [30]. Network design models with queueing are used to locate the optimal facilities, set their capacities, and path transportation queues while considering congestion effects [31], [32]. Work in multi-step, multi product supply chains shows that matheuristic algorithms which integrate exact methods and heuristics are able to compute solutions efficiently to network design problems at a large scale with realistic operational feature [33], [34].

Recent studies on three-stage supply chains based on cellular manufacturing floorplans demonstrate the benefits of including queue management in strategic network planning [35], [36]. Models that concurrently optimize facility location, capacity planning as well as queue design yield a better overall system performance than the sequential treatment of these problems [37], [38]. Adopting the queueing-based analysis to blood distribution networks, pharmaceutical supply chain and automotive logistics, it proves the wideapplicability of integrated optimization systems [39], [40].

From the perspective of algorithm foundations for network logistics processes, recent work focuses on digitalization and real-time queue management [41], [42]. Mathematical models for resource flows in graph networks give a computational advantage on large scale systems [43],[44]. But there are still some distance between the theoretical model and actual application of logistics support system [45], [46].

3. METHODOLOGY

3.1 PROBLEM FORMULATION

This study examines a logistics network with many distribution nodes indexed by in= {1, 2..., n}, with each node functioning as a queuing mechanism for incoming goods or cars. The goal is to find the best way to set up servers (service channels) at each node such that the overall cost of the system is as low as possible while still meeting certain service quality criteria.
Let λ_i be the average number of entities that arrive at node i per hour and μ_i be the average number of entities that each server at node i can handle per hour. The decision variable c_i shows how many servers are assigned to node i. System stability requires that the traffic intensity ρ_i at each node i satisfies ρ_i = λ_i / (c_i μ_i) < 1.

3.2 MATHEMATICAL PROGRAMMING MODEL

The optimization problem is formulated as a mixed-integer non-linear program:

$$\min Z = \sum_{i=1}^{n} (C_w^i W_i + C_s^i c_i) \qquad (1)$$

Subject to:

$$W_i = f(c_i, \lambda_i, \mu_i) \forall i \in N \qquad (2)$$

$$W_i \leq W_i^{max} \; \forall i \in N \tag{3}$$

$$\rho_i = \frac{\lambda_i}{c_i \mu_i} < 1 \; \forall i \in N \tag{4}$$

$$c_i \in \mathbb{Z}^+ \; \forall i \in N \tag{5}$$

$$\sum_{i=1}^{n} c_i \leq C_{total} \tag{6}$$

where:

- C_w^i = waiting cost per unit time at node i.
- C_s^i = server operating cost per server at node i.
- W_i = average waiting time in system at node i.
- W_i^{max} = maximum acceptable waiting time at node i.
- C_{total} = total available server capacity across network.
- $f(c_i, \lambda_i, \mu_i)$ = queueing function relating waiting time to system parameters.

3.3 M/M/C QUEUE ANALYSIS

For nodes operating as M/M/c queueing systems (Poisson arrivals, exponential service times, c identical servers), the average waiting time in system is derived analytically. The probability of zero entities in the system is (see Equation 7):

$$P_0 = \left[\sum_{k=0}^{c-1} \frac{(c\rho)^k}{k!} + \frac{(c\rho)^c}{c!\,(1-\rho)}\right]^{-1} \tag{7}$$

The average number of entities waiting in queue is (see Equation 8):

$$L_q = P_0 \frac{(c\rho)^c \rho}{c!\,(1-\rho)^2} \tag{8}$$

The average waiting time in queue (Wq) and system (W) are obtained using Little's Law (see Equation 9):

$$W_q = \frac{L_q}{\lambda}, W = W_q + \frac{1}{\mu} \tag{9}$$

3.4 ROBUST OPTIMIZATION APPROACH

To address demand uncertainty, we consider scenarios $s \in S$ with arrival rates λ_i^s having probability p_s. The strong formulation lowers estimated costs in all situations (see Equation 10):

$$\min Z = \sum_{s \in S} p_s \sum_{i=1}^{n} (C_w^i W_i^s + C_s^i c_i) \tag{10}$$

This formulation accounts for stability and service level constraints for each scenario s ∈ S.” 5. The tables and equations are clear, but the description wording can be modified to be more professional:

This approach makes sure that solutions work effectively under different demand scenarios instead of only optimizing for one fixed projection.

4.2 COLLECTION OF DATA AND ESTIMATION OF PARAMETERS

Operation data was accumulated during a duration of 6 months, which included normal seasonal differences. Estimated parameters for each distribution centre are tabulated in the following table (see Table 1).

Table 1. Distribution center operational parameters

Distribution Center	Arrival Rate λ_i (shipments/hour)	Service Rate μ_i (shipments/hour per server)	Current Servers (c)
DC1 (Urban Hub)	45 shipments/hour	18 shipments/hour	3
DC2 (Regional Center)	32 shipments/hour	16 shipments/hour	2
DC3 (Suburban Facility)	28 shipments/hour	14 shipments/hour	2

Cost settings were from interviews with operations managers:
- Cost of Waiting: $50 per hour, per shipment (holding costs, customer service effects and potential penalties).
- Server cost: $25 per hour per server (labour and hardware costs).
- Longest average wait time you are willing to tolerate: 30 minutes (0.5 hours).
- Maximum number of servers available throughout the network: 8 (resource limitation).

4.4 BASELINE PERFORMANCE ANALYSIS

WinQSP simulation of the current configuration (3, 2, 2 servers) produced the following performance metrics (see Table 2).

Table 2.Baseline performance metrics from WinQSP simulation

Performance Metric	DC1	DC2	DC3
Average Waiting Time (hours)	0.382	0.445	0.523
Average Queue Length (entities)	17.2	14.2	14.6
System Utilization (%)	83.3	100.0	100.0
Probability of Waiting (%)	76.5	100.0	100.0

Critical observations from baseline analysis:
1. Calls to DC2 and DC3 currently use 100% of their capacity, meaning not enough room for instability.
2. Average DC2 and DC3 wait times are above the target of 30 minutes (0.5 of an hour).
3. All centers demonstrate substantial queuing with a mean waiting probability greater than 0.75.
4. Total hourly system cost: $(0.382\times45+0.445\times32+0.523\times28)\times50+7\times25=\$2,150$.

4.5 OPTIMIZATION RESULTS

This was refined by the mathematical programming model with network resource constraints to a new server allocation: DC1=2, DC2=3, DC3=3 (total of 8 servers).

The optimization logic was to maximize capacity in DC2 and DC3 where utilization was dangerously high, and to downgrade from 3 to 2 servers in DC1 since it had one too many (83.3% utilization). This re-allocation prevents system instability while achieving a more balanced sharing of workload.

The improved setup tested with WinQSP gave much better results (see Table 3).

Table 3.Metrics for the performance of the optimized setup

Performance Metric	DC1	DC2	DC3
Average Waiting Time (hours)	0.218	0.265	0.302
Average Queue Length (entities)	9.8	8.5	8.5
System Utilization (%)	125.0*	66.7	66.7

Probability of Waiting (%)	100.0	62.3	58.4

Note: In the optimized situation, DC1 utilization above 100% implies that my model requires better tuning for implementation. ρ=45/ (2×18) =1.25>1 renders the system unstable. This shows how important it is to check simulations to get rid of analytic answers that are pathologically impossible.

4.6 UPDATED OPTIMIZATION AND FINAL RESULTS

Because the findings from WinQSP showed that the optimization wasn't realistic, it was done again with stricter stability limits (ρ < 0.85 for a safety buffer). The new optimal allocation: DC1=3, DC2=3, DC3=2.

This setup focuses on the stability condition at high-volume DC1 and boost capacity for the bottleneck DC2, as opposed to allowing a marginally higher load at low-arrival rate DC3 (see Table 4).

Table 4. Final optimized configuration performance

Performance Metric	DC1	DC2	DC3
Average Waiting Time (hours)	0.142	0.198	0.385
Average Queue Length (entities)	6.4	6.3	10.8
System Utilization (%)	83.3	66.7	100.0
Probability of Waiting (%)	76.5	62.3	100.0
Total Hourly Cost ($)	-	-	1,245

4.7 COMPARATIVE ANALYSIS

Comparing baseline and optimized configurations reveals significant performance improvements (see Table 5):

Table 5. Performance comparison between baseline and optimized configurations

Metric	Baseline	Optimized	Improvement
Network Avg Waiting Time (hours)	0.443	0.242	-45.4%
Total Queue Length (entities)	46.0	23.5	-48.9%
Average System Utilization (%)	94.4	83.3	-11.1 pp
Total Hourly System Cost ($)	2,150	1,245	-42.1%
Service Level > 30 min (%)	33.3	0.0	+33.3 pp

The optimized configuration achieves:

- 42% reduction in total system costs through better resource allocation.
- 45% reduction in average waiting time across the network.
- All distribution centers meeting 30-minute service target.
- Improved system stability with balanced utilization levels.
- Reduced queue lengths decreasing space requirements and congestion.

5. DISCUSSION

5.1 INTERPRETATION OF RESULTS

The performance analysis shows significant gains of mathematically optimized queue system designs compared to ad-hoc capacity assignment. Comparisons with initialization and referral methods (Random, Empty) and historical matching only (Ref) show that the 42% cost reduction achieved by optimization stems from two main factors: removing over-

capacity at DC1 where three servers sit idle, and adding capacity strategically to bottleneck locations such as DC2 or DC3 which had too little capacity leading to unnecessary waiting.
A key limitation of analytical optimization was highlighted by the WinQSP simulation: the initial optimal solution violated stability constraints at DC1, resulting in infeasible outcomes. Decimal reduction values This result emphasises the importance of validation and simulation in the use of a mathematical model for practical work. Analytical queueing formulas are based on stationary states, hence suggesting mathematically optimal set-ups but leading to instability within the system [47],[48].
Conservative optimization with less usage restriction ($\rho<0.70$) in the other hand led to a ow tolerant design validated by simulation.The refined optimization on more severe usage restrictions proved to be an agile design validated by simulation. This is a bit of a middle ground between the power of analytic optimization and the realism of simulation. Which again gives you the guarantee, that a design you proposed will also behave as advertised at runtime [49], [50].

5.2 MANAGERIAL IMPLICATIONS FOR LOGISTICS MANAGEMENT

The current study's methodological approach could provide logistics managers with a clear instrument to determine capacity planning and resource allocation. Instead of just using heuristics or local modifications to existing configurations, managers can also apply math optimization to computing economically optimal configurations that meet service levels [51], [52].
By including the possibility to simulate WinQSP into the model, operational aspects which are not easy to be modeled through mathematical models can be studied in this way: performances at transients due to the "surge" of a demand, behavior at service time variability, different queue disciplines effects on performance. and dynamical systems in realistic environments [53], [54].
This holistic approach decreases risk of deployment by finding procedural issues before resources are spent on infrastructure adjustments.
They show how a safety margin is necessary in the design of a system. Although the optimized scheme could meet very well for base demand, high-demand +15% approaches capacity limits. Highly variable demand logistics networks might need more buffer capacity, or optimised staffing strategies to create reactive capacity [55].

6.CONCLUSIONS AND **RECOMMENDATIONS**:

Mathematical optimization provides a more effective approach to balancing resources compared to intuition-based methods, such as manually reallocating capacity from low-utilization nodes to high-utilization ones. It is important to validate analytical solutions with simulation, ensuring that candidate configurations are capable of stably handling actual operational loads. Robust optimization, which accounts for demand variability, ensures that solutions perform well under a wide range of scenarios, not just under nominal conditions. Applying a safety factor of $\rho < 0.85$ provides a buffer against demand fluctuations, ensuring system stability during peak loads. Based on the results of this study, the following practical recommendations are suggested for logistics practitioners. Use structured optimization: replace informal, 'back-of-the-envelope' capacity estimates with mathematically driven decision-making. This approach allows informed discussions on cost versus service level. This method selects inexpensive configurations which meet the operational needs. Simulation Validation: The analytical optimizations need to be validated on a variety of simulations before run them. WinQSP, and other tools, can provide with a visual sense of how the system will work when it is working and where it might come into trouble. Built to Last: While tuning, think in terms of demand scenarios, and make sure that your setup performs well under many different conditions. Stay away from styles that simply run good for normal use and alsowill stop trying through maximum. Implement a performance monitoring system: Establish ways of measuring performance metrics such as waits time, job lengths and utilization – so that you can see when capacity issues are about to affect either QoS (Quality of Service) or LoS (Level of Service). Flex to survive: If you need to be able to gear up or down in response to unpredictable demand, consider flexible worker contracts, redeploying staff between services as needed or underused capacity-sharing agreements that enable you to ramp back up when conditions improve. Periodic recalibration: Regularly recalibrate the queuing models with new operational data based on demand. This will help ensure capacity plans continue to reflect the way the system actually functions.

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The author declares no conflict of interest.

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