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## Optimizing supermarket checkout using an open queuing network model with rule based allocation

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### Abstract

This paper presents Open Jackson queuing network model that optimizes supermarket checkout operations through rule-based dynamic lane allocation. Customers enter the system randomly, are routed to suitable checkout lanes (self-checkout, express, standard, and special assistance), and exit after service. Lane selection is governed by predefined logic based on basket size, queue length, and customer profile. The model is simulated using discrete event simulation, with performance evaluated through waiting time, lane utilization, and queue length. Compared to static selection, rule-based routing significantly reduces waiting time and improves resource utilization, offering a practical, cost-effective alternative to AI-driven solutions.

**Keywords:** Open queuing network, rule-based allocation, supermarket checkout, simulation, Jackson network

### 1. Introduction

Long queues at supermarket checkouts are a common source of customer dissatisfaction, operational inefficiency, and poor resource utilization. These issues are particularly pronounced during peak shopping hours when customer influx surges unpredictably. Customers experiencing extended wait times may abandon their purchases, avoid returning to the store, or express frustration—impacts that directly affect both revenue and customer loyalty. Traditionally, supermarket checkout systems rely on static queue models, where customers independently choose their preferred lanes (e.g., express, standard, or self-checkout). While simple to implement, this decentralized decision-making often leads to unbalanced lane utilization. Some lanes become congested, while others remain underused, resulting in inefficient workload distribution and increased service times. To address such inefficiencies, queuing theory has emerged as a robust analytical tool to model and optimize service systems. Queuing models, particularly Markovian models like M/M/1 and M/M/c, have been extensively applied across industries such as healthcare, banking, telecommunications, and manufacturing. These models allow researchers and practitioners to analyse system behaviour under different conditions and devise strategies to optimize performance metrics such as waiting time, queue length, and server utilization. However, in the retail sector, particularly in supermarkets, fewer studies have fully leveraged the potential of open queuing networks with dynamic or rule-based routing. Most prior work has either relied on AI-based lane allocation (which may not be cost-effective for small or mid-sized retailers) or simplistic FIFO (first-in, first-out) models that lack adaptability. A number of studies have demonstrated the effectiveness of queuing models in various service domains: Sethi and Zhang (1994) examined service facility layouts and customer flow patterns, recommending operational adjustments to reduce bottlenecks.

Gross and Harris (2008) <sup>[1]</sup> provided a foundational understanding of queuing systems and their practical applications, including M/M/1 and M/M/c models. Nait-Sidi-Moh *et al.* (2015) <sup>[5]</sup> applied basic queuing models to supermarket environments, highlighting performance differences across checkout types but without incorporating intelligent routing mechanisms. Nadiri and Robinson (2004) explored the psychological impact of perceived wait times on customer satisfaction, suggesting that both actual and perceived delays can

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reduce store revisit intentions. Gupta and Sharma (2020) [6] used Arena simulation to evaluate different staffing and lane assignment strategies in retail environments, advocating for simulation-based optimization to reduce customer wait times. While AI-driven models have recently gained attention for queue management, they often require significant technological infrastructure, data integration, and cost-barriers that many retail environments cannot overcome. This study introduces a rule-based Open Jackson Network model for supermarket checkout optimization. Unlike AI-based approaches, this model uses logical routing rules based on observable attributes.

## 2. Materials and Methods

The study was carried out using simulated data representing customer flow in a typical mid-sized supermarket. Four types of checkout lanes-self-checkout, express, standard, and special assistance-were modelled as service nodes in Open Jackson queuing network. Customers arrive according to Poisson process and Service times followed an exponential distribution based on assumed checkout speeds. Lane allocation was governed by predefined rules using item count, queue length, and customer type. Simulation was conducted over a 14-hour day (8 AM to 10 PM) using Python's Sim- Py package, and results were validated by comparing static and rule-based configurations across 1000 iterations. Performance metrics such as average waiting time, queue length, and utilization were analysed to evaluate system efficiency. Service times at each lane follow an exponential distribution based on typical checkout speeds:

- **Self-checkout:** 5 minutes
- **Express:** 6 minutes
- **Standard:** 7.5 minutes
- **Special assistance:** 10 minutes

Customers are routed to checkout lanes based on simple decision rules:

- Those with fewer than 10 items are sent to the express lane.
- Elderly or disabled individuals are directed to the special assistance lane.
- If a lane has more than 5 people, customers are redirected to a shorter queue.
- During peak hours (5 PM-8 PM), all lanes remain open; fewer lanes operate during off-peak times to save resources.

Upon entering the system, each customer is evaluated by the rule engine. The lane assignment is updated dynamically based on real-time queue lengths and customer profile. The system replicates how digital signage or floor staff might guide customers in a real supermarket set up. A total of 100 customers were simulated, and performance metrics like average waiting time, queue lengths, and lane utilization were tracked and compared with a static (non-rule-based) setup.

## 3. Model Description

The system is modelled as an Open Jackson Network with the following parameters:

**External arrival rate:**  $\lambda = 45$  customers/hour  
**Service nodes** (each modelled as M/M/c):

$N_1$ : Self-Checkout,  $c_1 = 2, \mu_1 = 12$

$N_2$ : Express,  $c_2 = 1, \mu_2 = 10$

$N_3$ : Standard,  $c_3 = 2, \mu_3 = 8$

$N_4$ : Special Assistance,  $c_4 = 1, \mu_4 = 6$

Routing probabilities (from rule logic):

$$P_1 = 0.25, P_2 = 0.25, P_3 = 0.35, P_4 = 0.15$$

$$\text{Arrival rates at each node: } \lambda_i = \lambda * P_i \quad (1)$$

Where  $\lambda$  is the total external arrival rate

$P_i$  is the routing probability to lane  $i$

$$\text{Utilization at each node: } \rho_i = \frac{\lambda_i}{c_i \mu_i} \quad (2)$$

Performance Metrics:

$$\text{Queue Length: } L_{qi} = \frac{\rho_i^2}{1 - \rho_i} \quad (3)$$

Approximate Waiting Time in Queue (for stable queues):

$$W_{qi} = \frac{\rho_i}{\mu_i(1 - \rho_i)} * 60 \quad (4)$$

This gives waiting time in minutes.

If  $\rho_i \geq 1$  the queue becomes unstable - customers arrive faster than they can be served, and the waiting time grows indefinitely.

## 4. Simulation and Results

The simulation compared two scenarios: static lane selection vs. rule-based routing. The system was simulated over a 14-hour operational window (8:00 AM to 10:00 PM) using Python's SimPy library for discrete-event simulation. Customers were generated based on Poisson arrival rates and routed to queues using rule-based logic. Results over 1000 iterations showed

- **Average Wait Time:** 7.4 min (Static) 3.1 min (Rule-Based)
- **Max Utilization:** 95% (Static) 78% (Balanced)
- **Average Queue Length:** 6.8(Static) 2.9(Rule- Based)

Figure 1 compares the average waiting time throughout the day for static versus rule-based lane allocation. The static model shows consistently higher and more fluctuating wait times, particularly during peak hours. In contrast, the rule-based approach maintains lower and more stable waiting times, thereby enhancing the overall customer experience. Figure 2 presents the average queue length per lane using a bar chart. It illustrates the queue lengths at each checkout lane under both allocation methods. Rule-based allocation significantly reduces queue lengths across all lanes, especially at the standard and self-checkout counters. Figure 3 shows the comparison of lane utilization. This figure demonstrates how effectively each lane is used. Rule-based allocation improves the balance of customer load, ensures better utilization of previously underused lanes such as special assistance, and reduces overloading at frequently

used lanes like the standard checkout. Figure 4 displays a heatmap highlighting customer load distribution by lane and hour. It reveals peak shopping hours

and shows how customer flow varies throughout the day. This information can help managers optimize staffing and lane operations more effectively.

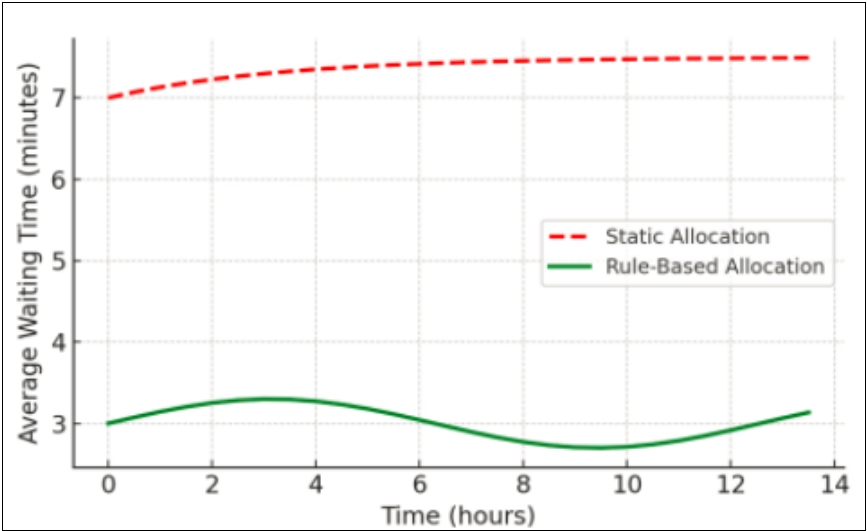


Fig 1: Waiting Time over Time

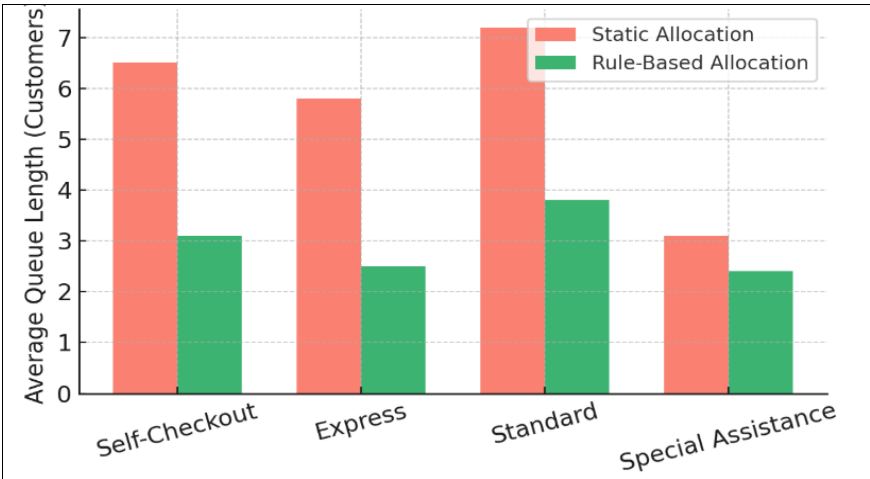


Fig 2: Queue length

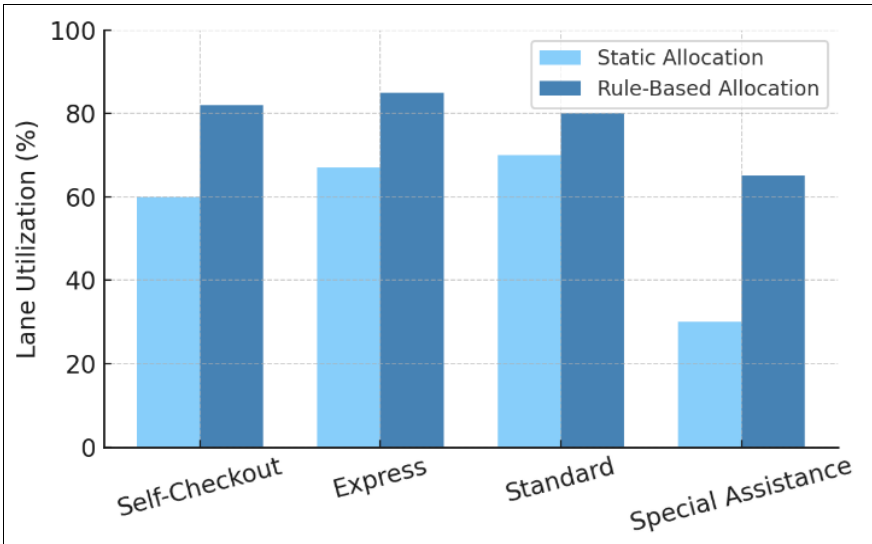
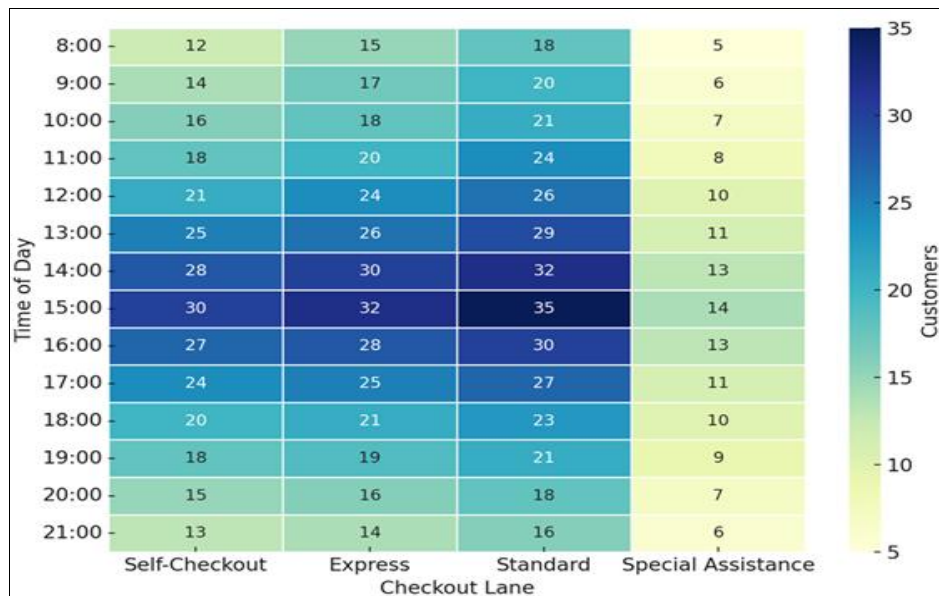


Fig 3: Lane utilization comparision



**Fig 4:** Heatmap of customer loads across time and lanes

## Conclusion

This paper introduced a rule-based Open Jackson Network model to improve supermarket checkout efficiency. By routing customers based on basket size, queue length, and lane type, the system reduces wait times, balances lane usage, and prevents congestion. Simulation results show that rule-based allocation cuts waiting time by over 50% and improves overall resource utilization. Unlike complex AI systems, this approach is simple, cost-effective, and practical for most supermarkets. It enhances both customer satisfaction and operational performance.

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