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QUANTIFYING CASE FLOW EFFICIENCY IN KENYA'S EMPLOYMENT AND LABOUR RELATIONS COURTS: A MULTI-STAGE QUEUEING MODEL APPROACH

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ABSTRACT: *Judicial efficiency is a key pillar for timely justice delivery and socio-economic stability. This study applies a Multi-Stage Queueing Model to assess case flow efficiency in Kenya's Employment and Labour Relations Court (ELRC). By analyzing five years of caseload data (FY2019/20–2023/24), the study models each stage, filing, pre-trial, hearing, determination, and execution/appeals, as an M/M/c system. The analysis reveals significant bottlenecks at the pre-trial and determination stages, with server utilization rates exceeding 90% and average waiting times far above acceptable thresholds. Conversely, the filing and execution stages exhibited relatively smooth flow with lower congestion levels. These findings highlight imbalances in resource allocation and process design. The study offers a data-driven framework for optimizing judicial operations, reducing backlogs, and improving service delivery in the ELRC.*

KEYWORDS: *Judicial efficiency, Queueing theory, M/M/c Case flow analysis, ELRC- Kenya*

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I. INTRODUCTION

Judicial efficiency is a fundamental pillar of access to justice and economic stability. Courts that resolve cases promptly uphold the rule of law, promote investor confidence, enhance the ease of doing business, and maintain social order, thus contributing to economic growth. An efficient judicial system is particularly vital in employment and labour relations, where unresolved disputes can lead to workplace disruptions, increased legal costs, and economic instability. Beyond its core mandate of adjudicating disputes, the Judiciary plays a vital role in promoting social harmony and people-centered justice. It fosters inclusive and accessible conflict resolution mechanisms that are responsive to the needs of all citizens, including marginalized groups. As a connector of justice champions, the Judiciary strengthens community relationships, promotes fairness, transparency, and accountability, and empowers citizens through collaboration with civil society and other justice sector stakeholders. Additionally, as a facilitator of dialogue, it encourages constructive discussions on justice issues and works proactively with stakeholders to prevent disputes, empowering communities while upholding human dignity [1].

Despite these important roles, many legal systems, including Kenya's, face persistent delays in case resolution, raising concerns about their ability to deliver timely justice. One of the fundamental challenges in Kenya's judiciary is the imbalance between case inflow (demand for court services) and judicial capacity (available judges and court resources). These delays in case processing are often attributed to an insufficient number of judges, procedural inefficiencies, and administrative constraints. As a result, litigants endure extended waiting periods before their disputes are resolved, exacerbating tensions in labour relations and affecting economic productivity.

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[1] Kenya Judiciary. Social Transformation through Access to Justice (STAJ) Blueprint, 2023-2033

The Employment and Labour Relations Courts (ELRC), a Court established under Article 162 (2) of the Constitution as a specialized superior court with the mandate to settle employment and industrial relations disputes[2], play a crucial role in resolving disputes between employers, employees, and trade unions. However, these courts have long struggled with case backlogs and prolonged resolution times. Such inefficiencies lead to increased legal costs, labour disruptions, and reduced public confidence in the judiciary.

This underscores the need for strategic interventions such as optimized case management, judicial staffing adjustments, and digital workflow enhancements to improve case resolution rates and reduce delays in the resolution of employment and labour disputes. However, there is limited research on how multi-server queueing models can be applied in Kenya's ELRC to quantify congestion and inform judicial policy.

The study applies the Multi-Stage Queueing Model to analyze case flow efficiency in Kenya's ELRC. This model accounts for the various stages of case processing, including filing, hearings, rulings/judgments, and appeals, to better understand the congestion and inefficiencies within the system. By quantifying judicial delays and resource utilization, this study seeks to inform policy interventions that could help reduce case backlogs and improve resource allocation within the ELRC. Unlike previous studies on judicial inefficiencies in Kenya that have relied primarily on descriptive statistics and anecdotal evidence, this research employs a multi-stage queueing approach to provide data-driven insights into judicial efficiency. The findings will inform policy interventions to reduce case backlogs, improve resource allocation, and strengthen judicial productivity in Kenya's ELRC while supporting the Judiciary's broader mission of fostering social harmony and people-centered justice.

II. LITERATURE REVIEW

Queueing theory has been widely applied across various service sectors, including healthcare, banking, and emergency services, to optimize resource utilization and minimize congestion. However, its application in the judicial system remains limited. While courts operate similarly to service systems with fluctuating case arrivals and constrained processing capacities, most studies on judicial efficiency rely on descriptive statistics and qualitative assessments. This study seeks to fill this gap by applying a Multi-Stage Queueing Model to assess case flow efficiency in Kenya's ELRC.

Previous studies have applied queueing models in different sectors, including healthcare, banking, and emergency response services to understand resource utilization and performance optimization. Olaniyi (2004) observed that multi-channel queue systems were preferred over single queues in banking due to cost and customer satisfaction implications. A case study of the First Bank of Nigeria demonstrated that a single-server system was ineffective when the arrival rate exceeded the service rate. While a four-server system eliminated waiting times, it was not cost-optimal. The study recommended a three-server system as a balanced solution for cost efficiency and customer service improvement.

Khaskheli et al. (2020) applied the M/M/C queueing model to optimize performance in hospital outpatient departments (OPDs) in Pakistan. They determined optimal staff levels by analyzing arrival rates, service rates, and system congestion. The study used Rockwell Arena software for simulation and TORA optimization software for performance measurement, recommending additional service providers to reduce patient wait times.

Similarly, Segun (2020) conducted performance modelling of healthcare service delivery using queueing theory at the Adekunle Ajasin University Health Centre, Nigeria. Through simulation-based analysis, the study revealed that patient congestion increased when service capacity remained static despite rising arrivals. A Python-based model was used to simulate the impact of policy interventions, showing that increasing service providers could significantly reduce delays.

Nor & Binti (2018) applied queue theory and simulation to analyze patient flow in a Malaysian public health clinic. Using ARENA software, they modelled patient wait times and system utilization, showing that service capacity

[2] 162 (2) of the Constitution of Kenya, 2010

constraints contributed to excessive delays. Their findings highlighted the role of stochastic models in improving service efficiency.

Shastrakar and Pokley (2017) further explored key queue metrics, including arrival rates, service rates, system utilization, and patient queue lengths. Their analysis demonstrated that during high system utilization, excessive wait times became a chronic issue, reinforcing the importance of capacity planning in congestion-prone service environments. Rotich (2016) examined the impact of queueing theory on emergency medical services at Moi Teaching and Referral Hospital (MTRH), Kenya. Using the M/M/S model, the study estimated optimal ICU bed capacity to reduce patient queue lengths and minimize waiting costs. The findings showed that increasing available ICU beds from 6 to 18 reduced the patient backlog and total system costs, demonstrating the potential of queueing-based interventions to improve service efficiency.

In the judicial context, Oghenekevwe et al. (2021) applied M/M/2 and M/M/3 queueing models to evaluate delays in Nigeria's magistrate courts within the Onitsha Magisterial District. The study focused on criminal cases and compared the efficiency of two- and three-server systems with identical and parallel queues. Results showed that the two-server model was more efficient due to lower idle time and better utilization of judicial resources emphasizing that delays in criminal case resolution may not solely be attributable to limited server capacity and that increasing the number of courts without strategic planning could lead to resource wastage.

While these studies are insightful, they rarely apply multi-stage queueing models to judicial systems. This study will expand on existing research by considering the different stages of case processing within the ELRC and analyzing how delays at each stage affect overall system performance.

III. METHODOLOGY

Queueing theory studies the behaviour of waiting lines, and it is useful in analyzing systems where customers arrive randomly for service at different stages of processing. In this study, we apply a Multi-Stage Queueing Model to assess case flow efficiency within Kenya's Employment and Labour Relations Court (ELRC). This approach accounts for multiple stages of case processing, including filing, pre-trials, case hearings, case determination, and executions or appeals, offering comprehensive view than traditional single-stage models.

Multi-Stage Queueing Framework

The Multi-Stage Queueing Model extends traditional queueing theory by considering multiple stages in the service process. In this study, each stage of case processing is modelled as a separate queueing system, each with its own arrival rate, service rate, and number of servers. This allows for a detailed analysis of bottlenecks and delays at each stage of the case processing cycle. The stages in case processing in Kenya's Employment and Labour Relations Court (ELRC) are:

a. **Case Filing** – The initial stage when cases are filed and registered.
b. **Pre-Trials** – foundational stages where Preliminary issues and document exchanges are done and the case is considered ready for trials
c. **Hearings** – Cases proceed to hearings where judges process the cases.
d. **Determinations** – After hearings, cases are adjudicated, and judgments or rulings are made.
e. E**xecution/Appeals (Optional)** – case outcome executed or go through the appeals process if applicable.

Each stage is modeled as a separate M/M/c queueing system (Markovian arrival and service process with multiple servers). Cases must pass through each stage in sequence, with the output of one feeding into the next

Data Sources

Data for this study were obtained from the Directorate of Strategy, Planning, and Organizational Productivity of the Judiciary, Kenya. The dataset covers 5 - Financial Year (FY 2019/20 to FY 2023/24), including case filings, resolutions, average durations at key stages (hearing, pre-trial, determination), and the number of judges serving during each financial year. Table 1 summarizes the dataset used in the model.

Table 1: *Statistics for the Employment and Labour Relations Court, FY2019/20–FY2023/24*

Financial year	Filed cases	Concluded cases	Hearing duration	Pretrial duration	Determination duration	No. of judges
2019–2020	2,312	3,900	180 days	75 days	120 days	15
2020–2021	5,100	4,200	170 days	70 days	115 days	17
2021–2022	5,500	4,800	160 days	65 days	110 days	19
2022–2023	5,900	5,300	150 days	60 days	100 days	21
2023–2024	6,200	5,900	140 days	55 days	95 days	23

Source: Directorate of Strategy, Planning, and Organizational Productivity, Judiciary of Kenya.

Model Assumptions

The study makes the following assumptions regarding the case flow within the ELRC:

1. Poisson Arrival Process: Case arrivals at each stage follow a Poisson distribution, implying that case filings, hearings, rulings, and appeals occur randomly but at a consistent average rate.
2. Exponential Service Times: The service time at each stage (i.e., the time it takes to process a case at each stage) follows an exponential distribution, meaning service times are random but with a constant average service rate.
3. Multiple Servers: Each stage of case processing has multiple servers (e.g., judges), which allows multiple cases to be processed concurrently.
4. Sequential Processing: Cases must pass through each stage in sequence (filing → pre-trials → hearings → determination → execution/ appeals).
5. Queue Discipline: cases are handled as First-Come, First-Served (FCFS), with exceptions for priority cases (e.g., certificates or injunctions).

Performance Metrics and Notations

Symbol	Description
λ	Mean arrival rate (cases filed per unit time)
μ	Mean service rate per server (cases resolved per unit time)
c	Number of servers (e.g., judges, clerks)
ρ	Utilization factor ($\frac{\lambda}{c\mu}$)
P_0	Probability that there are no cases in the system (all judges are idle)
P_n	Probability of having exactly n cases in the system
L_q	Average number of cases in queue (waiting to be heard)
L	Average number of cases in the system (queue + service)
W_q	Average waiting time in queue (excluding service)
W_s	Average service time per case
W	Total time a case spends in the system ($W_q + W_s$)
η	Total number of cases filed during the observation period
θ	Total number of cases concluded
T	Throughput (effective processing rate) ($c\mu(1 - P_0)$

IV. QUEUEING EQUATIONS AND SYSTEM METRICS

The model applies the following empirical formulations:

Case Arrival Rate (λ)

$$\lambda = \frac{\eta}{\tau}$$

Where:

- η = Total number of cases filed
- τ = Total observation period (e.g., per day)

Service Rate (μ)

$$\mu = \frac{\theta}{\tau}$$

Where:

- θ = Total number of cases resolved
- τ = Total observation period (e.g., per day)

Number of Servers (c)

- c = Number of Judges in the Employment and Labour Relations Court (ELRC)

System Utilization (ρ)

$$\rho = \frac{\lambda}{c\mu}$$

Where:

- λ = Case arrival rate
- μ = Average service rate per judge
- c = Number of judges (servers)

Interpretation of ρ:

- $\rho < 1$ indicates a stable system.
- A high ρ value suggests overburdened judges and long wait times.
- A low ρ value suggests underutilized judges and inefficiency.

The utilization factor ρ measures how busy the judicial system is. A system is considered stable if:

$$0 \leq \rho < 1$$

This condition ensures that cases do not accumulate indefinitely.

Expected Waiting Time in Queue (W_q)

Using Little's Theorem:

$$L = \lambda W$$

Where:

- L = Average number of cases in the system
- λ = Case arrival rate (cases filed per unit time)
- W = Average time a case spends in the system (including waiting and service time)

Derivation using Little's Law:
From Little's Law:

$$W_q = \frac{L_q}{\lambda}$$

Where:

- L_q = Expected number of cases in the queue
- λ = Case arrival rate

Substituting L_q from the Erlang-C formula:

$$L_q = \frac{P_0 \left(\frac{\lambda}{\mu}\right)^c \rho}{c!(1-\rho)^2}$$

Thus, the expected waiting time in the queue becomes:

$$W_q = \frac{P_0 \left(\frac{\lambda}{\mu}\right)^c \rho}{\lambda c!(1-\rho)^2}$$

This equation estimates the average time a case waits in queue before being assigned to a judge.

Probability of No Cases in the System (P_0): The system is modeled as a birth-death process:

- Case arrival rate remains constant: λ
- Service rate depends on the number of cases (η):
  - If $\eta < c$: Total service rate = $\eta\mu$
  - If $\eta \geq c$: Total service rate = $c\mu$

Let P_η be the probability of having η cases in the system.
For $\eta = 0$ (empty system):

$$\lambda P_0 = \mu P_1 \quad \Rightarrow \quad P_1 = \frac{\lambda}{\mu} P_0$$

For $1 \leq \eta < c$:

$$P_\eta = \frac{\left(\frac{\lambda}{\mu}\right)^\eta}{\eta!} P_0$$

For $\eta \geq c$ (all judges are occupied):

$$P_\eta = \frac{\left(\frac{\lambda}{\mu}\right)^\eta}{c!\, c^{\eta-c}} P_0$$

Normalization Condition: Total probability must sum to 1:

$$\sum_{\eta=0}^{\infty} P_\eta = 1$$

Split into two parts:

$$\sum_{\eta=0}^{c-1} P_\eta = P_0 \sum_{\eta=0}^{c-1} \frac{\left(\frac{\lambda}{\mu}\right)^\eta}{\eta!}$$

$$\sum_{\eta=c}^{\infty} P_\eta = P_0 \cdot \frac{\left(\frac{\lambda}{\mu}\right)^c}{c!} \sum_{n=0}^{\infty} \left(\frac{\lambda}{c\mu}\right)^n$$

Probability of No Cases in the System (P_0)

Apply geometric series:

$$\sum_{n=0}^{\infty} r^n = \frac{1}{1-r}, \quad \text{for } |r| < 1$$

So:

$$\sum_{\eta=c}^{\infty} P_\eta = P_0 \cdot \frac{\left(\frac{\lambda}{\mu}\right)^c}{c!(1-\rho)}$$

Combine and solve for P_0:

$$P_0 = \left[\sum_{\eta=0}^{c-1} \frac{\left(\frac{\lambda}{\mu}\right)^\eta}{\eta!} + \frac{\left(\frac{\lambda}{\mu}\right)^c}{c!(1-\rho)}\right]^{-1}$$

Throughput (Effective Case Processing Rate)

$$T = \text{Number of busy judges} \times \text{Service rate per judge} = c\mu(1 - P_0)$$

Alternatively, using $\rho = \frac{\lambda}{c\mu}$:

$$T = c \cdot \left(\frac{\lambda}{c\mu}\right) \cdot \mu = \lambda$$

Interpretation:

- If $\lambda < c\mu$: Stable system — all incoming cases are eventually processed.
- If $\lambda > c\mu$: Unstable system — backlog grows as cases accumulate.

Response Time (W)

The total time a case spends in the system:

$$W = W_q + W_s$$

Where:

- $W_q = \frac{L_q}{\lambda}$ is the average waiting time in queue.
- $W_s = \frac{1}{\mu}$ is the average service time.

Multi-Stage Queueing System Components:

Multi-Stage Queueing System Components in ELRC Case Flow:

- **Arrival Process:** Different case types (Claim, Appeal, Judicial Review, Petition, Application, CBA) represent multiple customer classes entering the system. Their arrival at the Filing stage follows a Poisson distribution, indicating randomness over time.
- **Service Process:** Each stage (Filing, Pre-Trial, Hearing, Determination, Execution/Appeal) serves cases at rates that follow Exponential distributions. This models variability in case processing time.
- **System Structure:** Each stage functions as an independent queue, characterised by:
  - Arrival rate λ
  - Service rate μ
  - Number of servers (judges/registrars)

  Cases proceed sequentially through these stages, modeling the justice pipeline.
- **Queue Discipline:** A First-Come, First-Served (FCFS) mechanism governs case handling, with exceptions for high-priority matters (e.g., constitutional petitions, urgent applications).

This model supports quantitative performance analysis (e.g., estimating waiting time, system utilization, and bottlenecks) to inform judicial resource optimization and efficiency.

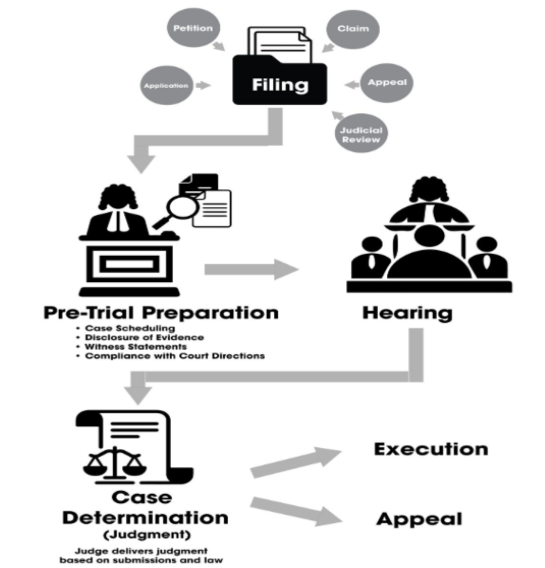

Figure 1: *Case processing flow in the ELRC*

Study Limitations

While this model treats each stage of the ELRC case process as an independent queue, in reality, stages are often interdependent. Delays in the pre-trial phase may cascade into hearings, while adjournments can cause disruptions not captured in a linear model. Additionally, the model assumes steady-state behaviour and exponential service times, which may not hold under all conditions. While necessary for analytical tractability, these simplifications may limit the model's precision.

V. RESULTS, INTERPRETATION AND DISCUSSION

This study employed a Multi-Stage Queueing Model to assess case flow efficiency in Kenya's Employment and Labour Relations Court (ELRC) over 5-financial years (FY2019/20 to FY2023/24). The model captured various stages in the case process, filing, pre-trial, hearing, determination, and execution/appeals, each modeled as a service point with distinct arrival rates λ) and service rates μ. System-wide performance indicators were computed under assumptions of a fixed number of judges per period and consistent daily working capacities.

The data was cleaned, processed, and analyzed using Python. Data cleaning involved handling missing values, standardizing date formats, and harmonizing case activity records across the five-year dataset. To support the multi-stage queueing model, the duration of each case process of filing, pre-trial, hearing, determination and execution/appeals was computed by calculating the time elapsed between each process. Pre-trial duration was derived from the interval between filing and the first hearing while hearing duration spanned from the first to the last hearing date. Determination duration captured the time from the final hearing to judgment delivery. These computations were automated using libraries such as Pandas and NumPy. Python scripts were developed to simulate the multi-stage queueing model and compute system performance metrics.

Table 2: Multi-stage queueing model results for ELRC (2019/20–2023/24)

Year	n	o	C	Pre-trial days	Hearing days	Deter. days	λ	μ	$c\mu$	ρ	W	W_q	L
2019–2020	2312	4358	12	146	100	1048	9.248	1.45	17.43	0.5305	1294	1294	11967
2020–2021	1552	3602	12	133	85	861	6.208	1.20	14.41	0.4309	1079	1079	6699
2021–2022	2684	2560	21	114	73	682	10.736	0.49	10.24	1.0484	869	867	9330
2022–2023	3893	6059	21	100	67	517	15.572	1.15	24.24	0.6425	684	684	10652
2023–2024	6201	10061	21	77	60	397	24.804	1.92	40.24	0.6163	534	534	13246

Source: Author (2025)

The results demonstrate the dynamic interplay between case inflows and judicial capacity across years

1. **Case Inflows Are Rising:** Case inflows increased significantly, from 10 cases/day in FY2019/20 to 25 in FY2023/24. reflecting rising demand for judicial services.
2. **Judicial Capacity Expanded:** The number of judges and system capacity $C\mu$ increased, notably in FY2021/22 and beyond. The capacity rose from 18 in FY2019/20 to 41 by FY2023/24.
3. **Utilization Rates Generally Stable**: System utilization (ρ) remained below 1 across all years except FY2020/21, where it spiked to 1.05. This overload likely reflects disruptions from the COVID-19 pandemic, reducing service capacity $C\mu$ and affecting efficiency.
4. **Persistent Queueing Delays:** Despite expanded capacity, average queueing time (Wq) remained high, with values exceeding 800 days in most years. This suggests that bottlenecks persist, particularly in the pre-trial and hearing stages occasioned by other factors such as case adjournments.
4. **Improved Performance:** With the highest filing rate recorded, FY2023/24 also showed notable improvement in system efficiency, average time in the system (W) declined to 534 days, a significant drop from 1294 days in FY2019/20.

These patterns indicate that while the ELRC is scaling its capacity in response to rising demand, internal workflow inefficiencies are hindering optimal performance. The results underscore the need for better case management practices to reduce inefficiencies.

VI. POLICY IMPLICATION AND RECOMMENDATION

The findings of this study highlight several policy opportunities to enhance case flow efficiency and service delivery in the Employment and Labour Relations Court (ELRC):

1. **Optimize Case Scheduling:** Introduce case scheduling systems and workflow automation to better manage transitions between stages, particularly from filing to pre-trial and minimize idle time.
2. **Strengthen Pre-Trial Process:** Persistent delays before trials suggest structural bottlenecks. Expanding the use of Alternative Dispute Resolution (ADR), mandatory conciliation, or mediation for suitable cases can ease pressure on formal hearings and shorten resolution timelines.
3. **Align Capacity with Stage-Specific Demand:** Increasing the number of judges alone is insufficient. Support staff, such as clerks, and legal researchers, should be deployed strategically to improve throughput at specific stages.
4. **Implement Stage-Based Performance Metrics:** Move beyond aggregate indicators (e.g., overall clearance rates) and adopt disaggregated stage-specific performance metrics. This approach can help identify and address delays more precisely and support evidence-based performance management.
5. **Leverage Data for Predictive Planning and Policy Management:** Use queueing and workload data to forecast congestion points and simulate policy impacts (e.g., circuit sittings) before implementation.

VII. CONCLUSION

This study applied a Multi-Stage Queueing Model to analyze case flow efficiency in Kenya's Employment and Labour Relations Court over five fiscal years. The findings show that while institutional capacity has improved, significant delays persist, particularly at the early stages of the case lifecycle. The persistent high queueing time and system delays underscore the need for stage-specific reforms, predictive planning, and broader adoption of data-driven case management. In conclusion, strategically targeting inefficiencies at each stage, complemented by capacity optimization and procedural reforms, can significantly enhance service delivery in the ELRC and move the judiciary closer to its goal of delivering timely and effective justice.

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