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MINIMIZING PATIENT LENGTH OF STAY IN THE EMERGENCY DEPARTMENT AT ANNA MEDIKA GENERAL HOSPITAL, MADURA

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Abstract

Prolonged length of stay (LOS) in emergency departments (EDs) negatively impacts patient care and operational efficiency. This study applies simulation modeling using ARENA software to analyze and optimize ED operations at Anna Medika General Hospital in Madura, Indonesia. Three improvement scenarios were evaluated: adding one nurse, one bed, and one general practitioner. The results show that adding a general practitioner reduced LOS significantly, from 184.64 minutes (3.08 hours) to 154.37 minutes (2.57 hours), making it the most effective intervention. However, the findings emphasize the importance of a holistic approach, as standalone interventions may only address isolated bottlenecks. Combining targeted staffing increases with process optimizations provides the most sustainable improvements. This study highlights simulation's value in evaluating operational strategies, enabling hospitals to make data-driven decisions that balance cost, resource allocation, and patient satisfaction.

Keywords: *emergency department; length of stay; simulation modeling; ARENA software; operational efficiency*

1. Introduction

Emergency departments (EDs) globally face challenges with prolonged length of stay (LOS), which affects patient outcomes and healthcare system efficiency. At Anna Medika General Hospital in Madura, the ED has seen increasing patient numbers, leading to longer LOS and overcrowding. This issue is particularly relevant in Madura, where healthcare infrastructure and resources are limited, and efficient service delivery is crucial to meeting patient needs. The LOS in this hospital is influenced by triage levels, resource availability, and organizational factors, as observed in similar studies (Dezfuli et al., 2022; Fekadu et al., 2022). Addressing these challenges locally requires tailored solutions that consider the specific conditions at Anna Medika.

Prolonged LOS has been linked to delayed treatment, increased hospital admissions, and higher mortality rates, especially among elderly patients and those requiring ICU admission (Ahmed et al., 2020; Bo et al., 2016; Lee et al., 2022). Reducing LOS is vital for improving patient satisfaction and enhancing care quality, particularly in low-resource settings like Madura (Angesti, 2015; Asuquo et al., 2023; Grover et al., 2018; Kim et al., 2018; Yim, 2016). Efforts to minimize LOS must address clinical, demographic, and organizational factors (Srivastava et al., 2022; Wehrmeister et al., 2019) while focusing on resource optimization.

Simulation modeling, particularly using ARENA software, is well-suited for analyzing complex ED processes and testing potential interventions. Unlike traditional methods, simulation enables a detailed exploration of patient flow and resource allocation, making it highly relevant for Anna Medika, where the exact causes of prolonged LOS are not fully understood (Brouns et al., 2015; Franklin et al., 2021). Process-driven discrete event simulation allows for testing various scenarios to identify practical solutions (Feng et al., 2024; Raunak et al., 2009). This method has proven effective in similar studies, offering actionable insights for improving ED efficiency (Shin et al., 2013; Terning et al., 2022).

Simulation studies have highlighted that LOS is influenced by resource availability, such as the number of beds, nurses, and doctors, as well as demographic variables and clinical acuity (Angler et al., 2024; Blanco et al., 2024; Fekadu et al., 2022; Ghanes et al., 2015). At Anna Medika, optimizing these factors requires considering both existing resources and potential improvements. Prior studies demonstrate the value of integrating multiple resources into simulation

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models for effective LOS reduction (Kenny et al., 2021; Shin et al., 2013).

In this study, simulation modeling was applied to evaluate the ED at Anna Medika General Hospital. The goal was to identify the most effective strategy to reduce LOS by testing scenarios such as adding doctors, nurses, and beds. These simulations provided data-driven recommendations tailored to the hospital's specific needs and resource constraints, ensuring relevance and applicability to the local context.

2. Methods

This study uses a structured quantitative approach to analyze and reduce LOS in the ED of Anna Medika General Hospital, Madura. The research combines simulation modeling with ARENA software and statistical analysis to identify and implement effective improvement strategies. This section outlines data collection, simulation model development, and scenario evaluation.

2.1 Data Collection

This study uses quantitative research methods to ensure accurate representation of actual conditions in the ED.

Primary Data Collection:

Primary data were collected through direct observation and manual recording of patient service times in the ED, from arrival to discharge. Data included timestamps for key process stages, such as triage, medical evaluation, diagnostic tests, and treatments. The data were categorized by service priority (e.g., triage levels) but did not include specific illness details to maintain patient confidentiality. Observations were conducted over a defined period to capture variations in service times during peak and non-peak hours.

Secondary Data Collection:

Secondary data were obtained directly from the hospital's administrative records. These included the hospital profile, details on the number of nurses assigned to the ED, nurse work schedules, and overall staffing patterns. These records provided contextual information to support the analysis of resource allocation and its impact on LOS. Clear documentation and systematic procedures ensured the reliability and accuracy of both primary and secondary data.

2.2 Study Design

Statistical methods validated the reliability of collected data. The study aimed to identify key causes of prolonged LOS. ARENA software was chosen for its capability to simulate complex healthcare processes. Service time distributions were tested to capture variability in ED operations.

2.3 Simulation Model Development

The simulation model replicated key ED processes, including triage, medical evaluations, diagnostic tests, treatments, and patient discharge or transfer. Verification ensured the model aligned with the real-world process flow. Validation compared simulated results with actual hospital data to confirm accuracy and reliability.

2.4 Improvement Scenarios

Three improvement scenarios were developed to address the identified inefficiencies in the ED processes:

a. **Adding Nurses**: To reduce waiting times during triage and transitions.
b. **Adding Beds**: To ease congestion and accommodate more patients during peak times.
c. **Adding Doctors**: To expedite medical evaluations and treatments.

Each scenario targeted specific bottlenecks observed in the ED.

2.5 Comparison and Analysis

The impact of each scenario on LOS was simulated. Key performance indicators (KPIs) included average LOS, standard deviation, and resource utilization. Statistical techniques such as mean comparisons and variance analysis were applied to assess outcomes. Feasibility and alignment with the hospital's operational constraints were also evaluated.

2.6 Success Criteria

The success of each scenario was measured by:

- Reduction in average LOS.
- Improved patient flow and resource utilization.
- Compliance with the Ministry of Health's recommended LOS standard.

2.7 Statistical Analysis

Simulation data were statistically analyzed using descriptive and inferential methods. Metrics such as average service times and standard deviations were calculated. The scenario with the shortest LOS and most significant operational improvements was selected for implementation. This structured approach ensures the proposed strategy is data-driven, practical, and tailored to the specific needs of Anna Medika General Hospital.

3. Results

The ED at Anna Medika General Hospital has nine nurses working in three different shifts: morning, afternoon, and night. The ED is also equipped with five beds for patient care. It is important to note that the ED at Anna Medika Hospital implements a triage system that prioritizes patients based on the severity of their conditions. There are four priority levels, namely:

1. Priority 1 (labelled red) is for patients who require immediate action due to critical medical conditions that, if not treated promptly, will threaten the patient's life or limbs.
2. Priority 2 (labelled yellow) is for patients who can wait for treatment because their condition is not life-threatening.
3. Priority 3 (labelled green) is for patients with minor injuries that can be treated on an outpatient basis.

Table 1. Patient Admitted to the ED (Source: Anna Medika General Hospital)

Priority	Number of patients	Average Length of Stay in the ED (hour)
1	44	15:30:09
2	255	6:53:38
3	128	2:34:45

Table 2. Value and Distribution Form of Service Time

No	Process	Distribution	Unit
1	Triage	2.5+WEIB (2.44,6.85)	minutes
2	Examination	3+WEIB (81.4,1.14)	minutes
3	Care actions	8+EXPO (95.1)	minutes
4	Specialist consultation	NORM (73.4,44.7))	minutes
5	Prescription issuance	4+192*BETA (1.07,2.67)	minutes
6	Discharge from the ED	TRIA 3,19.5,234)	minutes

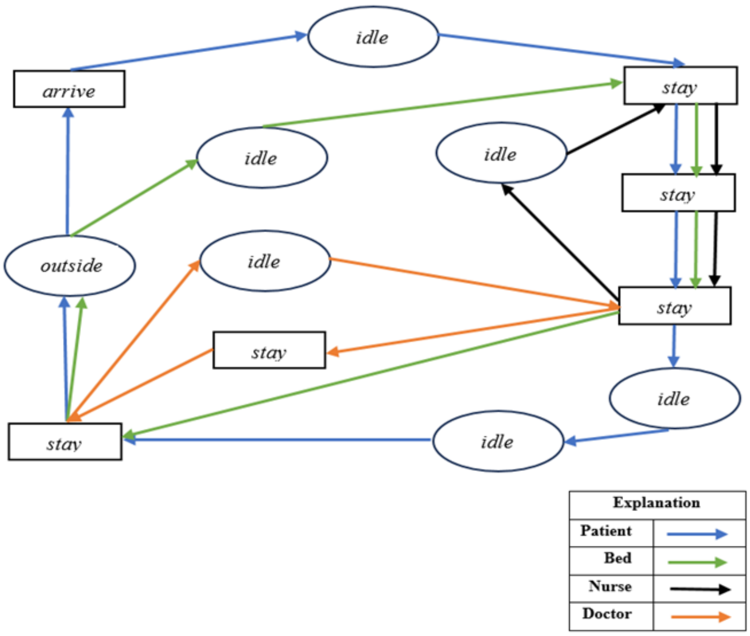

Figure 1. Activity Cycle Diagram for Patient LOS

Proposed Scenario #1 (PS #1)

4. Priority 4 (labelled black) is for patients who do not require treatment or have already passed away.

The service process in the ED of Anna Medika General Hospital begins with an initial assessment by the triage team to determine the patient's severity level. Next, the ED doctor will conduct an examination and make a diagnosis of the illness. Laboratory tests will be conducted to clarify the diagnosis. While waiting for the laboratory test results, the patient will remain in the ED. If the hospital has the capacity to provide further care, the patient will be transferred to the inpatient unit. However, if necessary, the patient may also be recommended for treatment at another medical facility that better meets their needs.

Based on the data from July 2023 at Anna Medika General Hospital, 427 patients received treatment in the ED, categorized into three priorities: priority 1, priority 2, and priority 3. This data can be seen in **Table 1**. The average service time for the ED for these three priority levels was 6 hours 29 minutes and 15 seconds, which exceeds the recommended length of stay (LOS) of 6 hours to prevent crowding in the ED. Therefore, this issue needs to be analyzed by identifying the causes of the prolonged patient time in the ED based on processes carried out in the ED such as examinations, treatments, specialist consultations, and other actions.

Data Distribution Testing

The collected service time data at the ED of Anna Medika General Hospital is subsequently tested for its distribution. The purpose of this determination is to identify the most suitable distribution type for each service time. **Table 2** is a summary of the data distribution results for patient service times in the ED of Anna Medika General Hospital using the input analyzer available in the ARENA software.

Activity Cycle Diagram

Figure 1 illustrates the Activity Cycle Diagram (ACD) for the service process in the ED of Anna Medika General Hospital, detailing the steps from the patient's arrival to their departure from the ED. The proposed first scenario model is to add one more nurse to the ED to provide care for ED patients. This is

Table 3. Initial Simulation vs Proposed Scenarios

No	Process	IS	PS #1	PS #2	PS #3
1	Triage	3.52	2.17	3.46	15.7
2	Examination	5.35	2.65	6.06	33.4
3	Care action	1.37	0.91	13.29	17.72
4	Specialist consultation	168.07	160.45	168.87	68.86
5	Prescription issuance	5.78	0.27	0.59	11.66
6	Discharge from the ED	0.55	2.42	0.43	7.56
	Total	**184.64**	**168.87**	**192.1**	**154.37**

because previously, 9 nurses worked in shifts, with 3 nurses per shift. We believe this addition aims to improve service quality, especially during the day and night shifts. Below is the comparison result between the initial simulation and the proposed improvement scenario. **Table 3** compares the average service time per process and total service time of initial simulation (IS) model with the average per process and total service time of first improvement scenario (minute), showing a reduction in total service time from 184.64 minutes (3.08 hours) to 168.87 minutes (2.82 hours).

Proposed Scenario #2 (PS #2)

The second scenario proposes the addition of one bed. We believe that this additional bed can be used for patients with priority 3 who, after treatment, can immediately leave the room to go home. **Table 3** compares the average service time per process and total service time of the initial simulation (IS) model with the average per process and total service time of the second improvement scenario (minute). The initial model shows a total ED service time of 184.64 minutes (3.08 hours), while Scenario #2 increased it to 192.1 minutes (3.2 hours).

Proposed Scenario #3 (PS #3)

The third scenario model adds one general practitioner in the ED, bringing the total number of doctors in the ED to two. **Table 3** compares the average service time per process and total service time of the initial simulation (IS) model with the average per process and total service time of the third improvement scenario (minute). The total ED service time decreased from 184.64 minutes (3.08 hours) to 154.37 minutes (2.57 hours).

4. Discussions

The following section delves into the interpretation of data distribution results and their implications for patient service times in the ED of Anna Medika General Hospital. It evaluates the impact of various improvement scenarios on service times, providing insights into how each proposed change affects overall efficiency. Lastly, the effectiveness of these changes is discussed, highlighting their potential benefits and limitations in optimizing ED operations and enhancing patient care.

4.1 Interpretation of Data Distribution Results and Their Implications

The data distribution results, presented in **Table 2**, offer valuable insights into the variability and characteristics of service times in the ED at Anna Medika General Hospital. By employing ARENA software's input analyzer, this study identified the statistical distributions best suited to model each service process, highlighting areas of inefficiency and variability. These insights serve as the foundation for optimizing operations and enhancing patient care.

The **Weibull distribution** for triage times, expressed as 2.5+*WEIB*(2.44,6.85), indicates that most assessments are completed within 5 to 10 minutes. However, occasional outliers extend significantly beyond this range, particularly during peak hours. This variability points to the need for adequate staffing to manage unpredictable durations and ensure a smooth flow of patients. Similarly, the examination process, also following a **Weibull distribution** (3+*WEIB*(81.4,1.14), reveals that while the majority of examinations are resolved within 80 to 90 minutes, more complex cases can take much longer. These findings emphasize the importance of strategic scheduling and capacity planning to ensure that examination rooms and diagnostic resources are available when needed.

In contrast, the **exponential distribution** for care actions (8+*EXPO*(95.1) suggests a predictable process where most tasks are completed swiftly, typically within 8 to 12 minutes. While the likelihood of prolonged care actions is low, the predictability of this process enables better scheduling and resource allocation. This efficiency contributes to smoother transitions between care stages, reducing overall delays in patient flow.

Specialist consultations exhibit a **normal distribution** (*NORM*(73.4,44.7), with an average consultation time of 73.4 minutes and a standard deviation of 44.7 minutes. This symmetric distribution reflects significant variability, with consultation times ranging from approximately 30 to 120 minutes. To address this, flexible scheduling is necessary to accommodate both shorter and longer consultations without disrupting other ED processes. Ensuring the availability of specialists during peak consultation periods is critical to maintaining efficiency.

The **beta distribution** for prescription issuance (4+192∗*BETA*(1.07,2.67) reveals a skewed pattern where most prescriptions are issued within 5 to 10 minutes, but some extend beyond 15 minutes due to complexity. This variability suggests the need for streamlined workflows and support systems for pharmacy staff to handle intricate prescriptions more efficiently. Addressing these delays can significantly reduce patient waiting times and enhance the discharge process.

Discharge times, modeled with a **triangular distribution** (*TRIA*(3,19.5,234), show a wide range of potential delays or accelerations. While the mode of 19.5 minutes indicates that most discharges occur promptly, the maximum value of 234 minutes underscores substantial inefficiencies in this stage. These delays could stem from coordination issues between ED staff and inpatient wards or external facilities. Streamlining discharge planning and communication can minimize these inefficiencies, ensuring timely bed turnover and accommodating incoming patients more effectively.

Together, these distributions provide a clear picture of the ED's operational challenges and serve as a guide for targeted interventions. Using ARENA software to simulate these processes enables hospital managers to evaluate the potential impact of changes before implementation. For example, improving triage and examination workflows can address the variability highlighted by their respective Weibull distributions, while optimizing specialist consultations and prescription processes can reduce delays in critical stages of patient care.

Each distribution reflects unique operational characteristics that, when addressed systematically, can significantly improve patient flow, resource utilization, and overall care quality. These findings underscore the importance of a data-driven approach to process optimization, ensuring that proposed improvements are both effective and sustainable.

4.2 Evaluation of Each Improvement Scenario's Impact on Service Times

The selected improvement scenarios—adding one nurse, one bed, and one general practitioner—were informed by the data distribution results, which identified key bottlenecks in ED operations. Each scenario addresses specific inefficiencies highlighted by the simulation model, and their combined impact offers insights into optimizing service efficiency.

Scenario #1: Adding One Nurse

Adding a nurse directly addresses delays in triage and examination stages, both characterized by Weibull distributions. These stages often experience variability, with occasional outliers causing extended wait times. By adding a nurse, the total service time was reduced from 184.64 minutes (3.08 hours) to 168.87 minutes (2.82 hours). This improvement demonstrates the value of additional nursing staff in managing patient loads more effectively during peak times, facilitating faster triage and smoother transitions. However, while effective in reducing delays, this scenario alone may not resolve inefficiencies in other stages.

Scenario #2: Adding One Bed

Adding a bed aims to alleviate congestion by increasing capacity, particularly during peak periods. The triangular distribution of discharge times reflects variability that adding a bed could potentially reduce. However, simulation results showed an increase in total service time to 192.1 minutes (3.2 hours). This suggests that while capacity is essential, adding a bed alone does not address underlying process inefficiencies. Additional factors, such as staff availability and streamlined workflows, are necessary to make this intervention effective.

Scenario #3: Adding One General Practitioner

Adding a general practitioner focuses on reducing delays in examination and care actions, stages with high variability and complexity (Weibull and exponential distributions). This scenario resulted in the most significant reduction in total service time, from 184.64 minutes (3.08 hours) to 154.37 minutes (2.57 hours). The presence of an additional GP reduced bottlenecks in critical stages, enabling faster evaluations and treatments. This highlights the importance of enhancing medical staff availability to improve patient flow and care quality.

4.3 Evaluation of Each Improvement Scenario's Impact on Service Times

The simulation results highlight that targeted staffing changes, such as adding nurses or general practitioners, can significantly enhance efficiency and patient care in the ED. However, implementing these changes in isolation risks addressing only surface-level issues without resolving deeper process inefficiencies. For example, while adding a nurse reduces the average LOS from 184.64 minutes to 168.87 minutes, it primarily alleviates delays in triage and examination stages. Similarly, adding a general practitioner provides the most substantial improvement, reducing LOS to 154.37 minutes, yet this intervention alone cannot address capacity constraints caused by bed shortages or inefficient discharge processes.

A holistic approach that combines multiple interventions offers a more comprehensive solution. The simulation underscores that increasing both medical and nursing staff simultaneously tackles multiple bottlenecks. By addressing triage delays with additional nurses and reducing examination and care times with an extra doctor, the ED can significantly improve patient flow across all stages. This combined strategy not only reduces LOS but also ensures resources are optimally utilized.

Financial and logistical considerations must guide these decisions. Adding a general practitioner incurs higher costs due to salaries and training but yields the largest reduction in LOS, directly improving patient satisfaction and outcomes. Conversely, adding a bed has minimal cost but shows an increase in LOS, from 184.64 minutes to 192.1 minutes, as it fails to address underlying issues like staff availability and discharge delays. These findings suggest that while capacity expansion is necessary, it must be paired with staff increases and process improvements to be effective.

The simulation results also emphasize the importance of aligning interventions with specific operational challenges identified through data distribution analysis. For example, the variability in triage times, captured by the Weibull distribution, supports the decision to add nurses during peak hours. Similarly, the high variability in examination and care times, modeled by Weibull and exponential distributions, justifies adding a general practitioner to manage complex cases more efficiently.

A combination of scenarios ensures that operational and quality objectives are met. Increasing both medical and nursing staff addresses immediate patient care bottlenecks while laying the foundation for sustained efficiency improvements. This integrated approach reduces the risk of merely shifting delays from one stage to another, as seen in scenarios that focus solely on capacity or staffing.

Simulations remain a vital tool for hospital managers, enabling them to test combined scenarios and predict outcomes before implementation. For instance, pairing the addition of a nurse with a general practitioner could be simulated to determine its overall impact on patient flow and resource utilization. These evaluations ensure decisions are evidence-based, minimizing risks and maximizing returns on investment.

To maintain long-term ED efficiency, continuous improvement processes are crucial. Regular updates to the simulation model with new data allow hospital managers to adapt to changing patient demands and operational dynamics. For example, variations in patient volume or changes in triage patterns can be incorporated to refine interventions proactively. This iterative approach ensures standardization, consistency in care delivery, and high patient satisfaction while maintaining cost-effectiveness.

In conclusion, the simulation results indicate that combining staffing enhancements with process optimization yields the most significant improvements in LOS and overall ED efficiency. By addressing multiple bottlenecks simultaneously and leveraging simulation tools for data-driven decision-making, hospitals can achieve sustainable and impactful outcomes that enhance both operational performance and patient care quality.

5. Conclusion

This study highlights the successful application of simulation methods to address prolonged patient length of stay (LOS) in the ED at Anna Medika General Hospital. By simulating and evaluating three improvement scenarios—adding one nurse, one bed, and one general practitioner—the research identifies adding a general practitioner as the most effective strategy. This intervention reduces LOS from 184.64 minutes (3.08 hours) to 154.37 minutes (2.57 hours), demonstrating the critical role of additional medical staff in managing complex cases and expediting treatment processes.

The findings provide actionable recommendations for hospital administrators aiming to optimize ED operations. Adding a general practitioner directly addresses bottlenecks in examination and care stages, significantly improving patient flow and satisfaction. This solution is particularly relevant for hospitals with similar resource constraints and patient demands. However, financial implications, including costs associated with recruitment, salaries, and training, must be evaluated to ensure the sustainability of this intervention.

While adding a nurse also reduced LOS to 168.87 minutes (2.82 hours), it primarily addressed delays in triage and transitions. Conversely, adding a bed increased LOS to 192.1 minutes (3.2 hours), highlighting that capacity improvements alone are insufficient without addressing underlying process inefficiencies. These findings emphasize the importance of combining multiple strategies to achieve meaningful improvements in ED efficiency.

The study further demonstrates the broader applicability of simulation as a decision-making tool for hospital management. Simulation enables the assessment of potential interventions in a risk-free environment, allowing managers to prioritize changes that offer the greatest impact. For hospitals, regularly updating simulation models with real-time data ensures continuous improvement, enabling proactive responses to emerging challenges such as fluctuating patient volumes or changing operational dynamics.

To implement these findings effectively, hospitals should adopt a holistic approach. Combining the addition of a general practitioner with other targeted improvements, such as increasing nursing staff or optimizing workflows, addresses multiple inefficiencies simultaneously. This integrated strategy enhances resource allocation, reduces bottlenecks, and improves overall care quality.

In summary, this research provides a practical, data-driven framework for reducing ED LOS and improving hospital performance. By leveraging simulation models, hospital managers can make informed decisions that balance cost, resource utilization, and patient care. These findings are directly applicable to hospitals seeking to enhance operational efficiency while maintaining high standards of patient care and satisfaction.

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