

OPTIMIZING CLASSROOM ALLOCATION USING MARKOV CHAIN MODEL FOR SHIFTED LECTURE SCHEDULES

NAHRUL HAYATI^{a*}, EKO SULISTYONO^b, BULAN PURNAMA UTAMI^c

^{a,c} *Mathematics Department, Batam Institute of Technology,*

^b *Mathematics Department, Tanjungpura University.*

email: nahrul@iteba.ac.id

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Abstract. *This study aims to optimize classroom allocation for shift lecture schedules at the Batam Institut of Technology (ITEBA) using a Markov chain model. Classroom utilization data from the Odd and Even Semesters of the 2024/2025 Academic Year were analyzed by defining four classroom usage states: occupied in the morning shift and vacant in the evening shift (OV), vacant in the morning shift and occupied in the evening shift (VO), occupied in both morning and evening shifts (OO), and vacant in both morning and evening shifts (VV). State transition analysis revealed patterns in classroom allocation dynamics between semesters, while steady-state analysis projected long term utilization. The results show a steady-state probability of 74.04% for the OO state (optimal utilization), but 15.48% of classrooms remain in the VV state (chronic under utilization). Based on these findings, the study recommends a classroom consolidation strategy based on complementary patterns, implementation of a digital reservation system, and optimization of single shift usage. This study concludes that the Markov chain model provides a scientific basis for strategic decision making in educational facility management.*

Keywords: Classroom Allocation, Markov Chain, Shift Lecture Schedules.

1. Introduction

Batam City, a major economic hub in Indonesia's Riau Islands Province, has experienced rapid growth, attracting a large productive-age population for work and business [1,2]. This dynamism has spurred significant demand for higher education, leading to establishment of numerous institutions to accommodate both recent high school graduates and working professionals [3,4,5,6]. Batam Institute of Technology (ITEBA), a leading private institution in the city, exemplifies this trend with a sizable student body across eight study programs [7,8]. To serve its diverse

*Corresponding author

population, ITEBA implements a flexible shifted lecture system, offering morning and evening sessions to provide accessible education without compromising quality [9,10].

While such shift enhance accessibility, they introduce significant operational challenges in managing physical resources. A primary issue is the frequent imbalance in classroom utilization, where certain rooms face overcapacity during one shift while remaining underutilized or vacant in another. This inefficiency leads to sub-optimal resource allocation and potential wastage of institutional assets [11,12,13]. Effectively optimizing classroom allocations is therefore crucial for improving operational efficiency and reducing costs within the university's shift system.

Despite the proven utility of Markov chain models in forecasting and optimizing complex systems across fields like economics [14,15] and genetics [16,17], their application in educational facility management remains relatively unexplored [18,19,20]. In broader educational scheduling research, more complex AI-based methods and multi-objective optimization frameworks have been explored for timetabling problems [21,22,23]. However, these often focus on generating optimal schedules from scratch, rather than diagnosing and predicting the long-term dynamics of existing allocation systems from limited historical data, which is the primary objective of this study. A review of existing literature reveals a clear gap, no prior research has explicitly employed this probabilistic model to analyze and optimize dynamic classroom allocation based on actual, time-varying usage patterns between lecture shifts. This study aims to fill that gap by developing a Markov chain model, following methodologies used in predictive scheduling analysis [24,25,26], to analyze transition probabilities between classroom states and calculate steady-state probability to predict long-term utilization trends at ITEBA.

The findings of this research are expected to provide a data-driven framework for predicting classroom usage patterns, enabling proactive and efficient space planning. By identifying the steady-state equilibrium, the institution can mitigate usage disparities and enhance operational efficiency. Ultimately, this study offers actionable recommendations for reducing resource waste and formulating effective, sustainable long-term space management strategies for ITEBA and similar institutions adopting shift-based systems.

2. Methods

2.1. Data Collection

The study employs a documentary analysis method, utilizing secondary data obtained from the official academic records of ITEBA, which serves as the research object. The data was collected retrospectively from the academic system (SIKAD). The use of this institutional data complied with privacy and ethical research guidelines. The data was anonymized and aggregated at the room-utilization level, containing no personal identifiers of students or faculty. Access was authorized by the ITEBA Academic Administration for this institutional efficiency study.

The datasets encompasses detailed records of classroom usage over two full academic semesters, the Odd (Ganjil) Semester and the Even (Genap) Semester of the

2024/2025 Academic Year. This time frame was selected to capture a complete and representative cycle of academic activities. The specific information extracted from the records includes:

- (1) Room Usage Schedule
Detailed lecture schedules data for each study program, which includes course code and name, name of the instructing lecturer, day and time of the lecture, and assigned location (classroom name or code).
- (2) Usage Status
The status condition of a classroom at a specific time slot, classified as occupied (the classroom has an officially registered lecture scheduled) and vacant (the classroom has no lecture schedule at the observed time slot).
- (3) Usage Time
The designation of the shift or session of room usage based on the lecture schedule, namely morning shift (lectures held during morning to afternoon operational hours) and evening shift (lectures held during afternoon to evening operational hours).

2.2. Data Analysis

The collected data on classroom usage will be analyzed using a Discrete-Time Markov Chain model [27]. The analysis will involve three main components, defining the state space, constructing the transition probability matrix, and performing a steady-state analysis. The key perspective of this analysis is to model the change in the utilization pattern of each classroom from the Odd Semester (Ganjil) 2024/2025 to the Even Semester (Genap) 2024/2025.

- (1) State Space Definition
The first step involves defining the state space, which represents the possible utilization patterns of a classroom within a single semester. The states are defined based on its consistent usage status across the shift system:
State 1 (OV): Occupied in the Morning Shift and Vacant in the Evening Shift,
State 2 (VO): Vacant in the Morning Shift and Occupied in the Evening Shift,
State 3 (OO): Occupied in Both Morning and Evening Shifts, and
State 4 (VV): Vacant in Both Morning and Evening Shifts.
The state space captures all possible utilization patterns for a classroom across the two-shift system.
- (2) Transition Probability Matrix Construction
The dynamic of classroom allocation from one semester to the next will be modeled using a transition probability matrix. This matrix, denoted as \mathbf{P} , is a square matrix where each element P_{ij} represents the probability of a classroom transitioning from state i in the Odd Semester (Ganjil) to state j in the subsequent Even Semester (Genap). The matrix is structured as:

Table 1. Schedule of ITEBA Classroom Usage for the 2024/2025 Academic Year

Room	Odd Semester				Even Semester			
	Morning Shift		Evening Shift		Morning Shift		Evening Shift	
	Occupied	Vacant	Occupied	Vacant	Occupied	Vacant	Occupied	Vacant
A302	✓		✓			✓		✓
A303		✓	✓			✓		✓
A305		✓	✓			✓		✓
A306		✓	✓			✓	✓	
A307		✓	✓			✓	✓	
A308		✓	✓			✓		✓
A309		✓	✓			✓	✓	
A311		✓	✓		✓		✓	
A312	✓		✓		✓		✓	
A313	✓		✓		✓		✓	
A314	✓		✓		✓		✓	
A315	✓		✓		✓		✓	
A316	✓		✓		✓		✓	
A317	✓		✓			✓	✓	
A404	✓		✓		✓		✓	
A405		✓		✓	✓		✓	
A406	✓			✓	✓		✓	
A407	✓		✓		✓		✓	
B208	✓		✓		✓		✓	
B209		✓		✓	✓		✓	
B211	✓		✓			✓		✓
B302	✓		✓		✓		✓	
B303	✓		✓		✓		✓	
B304		✓	✓		✓		✓	
B305	✓		✓		✓		✓	
B309	✓		✓			✓		✓
B311	✓		✓		✓		✓	
B312	✓		✓		✓		✓	
B313	✓		✓		✓		✓	
B314	✓		✓		✓		✓	
B315	✓		✓			✓		✓
Lab 1	✓		✓		✓		✓	
Lab 2	✓		✓		✓		✓	
Lab 3		✓		✓	✓		✓	

$$\mathbf{P} = \begin{bmatrix} P_{OV,OV} & P_{OV,VO} & P_{OV,OO} & P_{OV,VV} \\ P_{VO,OV} & P_{VO,VO} & P_{VO,OO} & P_{VO,VV} \\ P_{OO,OV} & P_{OO,VO} & P_{OO,OO} & P_{OO,VV} \\ P_{VV,OV} & P_{VV,VO} & P_{VV,OO} & P_{VV,VV} \end{bmatrix}$$

Each probability P_{ij} will be calculated empirically from the data using the maximum likelihood estimator: $P_{ij} = \frac{n_{ij}}{n_i}$, where:

- n_{ij} is the number of classrooms that were in state i in the Odd Semester and transitioned to state j in the Even Semester.
- n_i is the total number of classrooms that were in state i in the Odd Semester.

The matrix \mathbf{P} describes the semester to semester dynamics of how classroom utilization patterns change at ITEBA.

(3) Steady-State Analysis

The core of the analysis involves finding the steady-state probability vector, π . This vector represents the long-term equilibrium distribution of classroom utilization across the four states over many semester (e.g., over several academic years), assuming the transition probabilities remain constant. It is found by solving the system of equations:

$$\pi P = \pi,$$

subject to the constraint that the sum of all probabilities in π is 1:

$$\sum_{i=1}^4 \pi_i = 1,$$

where π_i is the steady-state probability for state i [17].

This system of equations will be solved using numerical computation methods (e.g., solving eigenvectors). The resulting steady-state probabilities are crucial for strategic planning. They predict the ultimate proportion of classrooms that will fall into each utilization category if current scheduling policies continue unchanged. This allows management to identify long-term inefficiencies and evaluate the need for policy interventions to achieve a more optimal and sustainable allocation of space.

3. Result and Discussion

3.1. Overview of Classroom Utilization Patterns

The initial analysis of classroom utilization at ITEBA for the 2024/2025 Academic Year (Table 1) reveals a distinct pattern between the two shifts. The data, summarized in Figure 1, shows that the evening shift consistently experienced higher occupancy than the morning shift across both semesters.

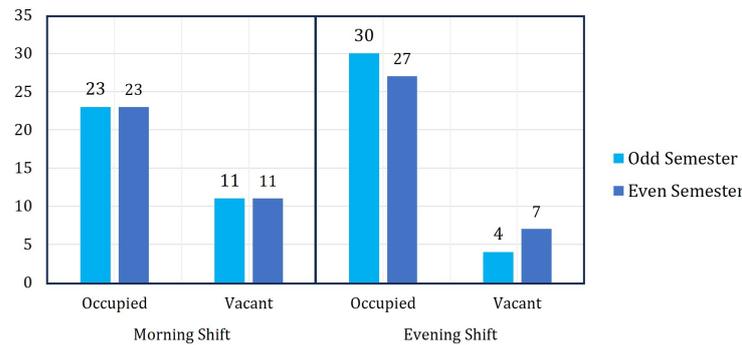


Figure 1. Classroom Utilization per Shift and Semester

Based on Figure 1, in the Odd Semester, the evening shift demonstrated remarkably high demand, with 30 out of 34 rooms occupied, resulting in a utilization rate of 88.2%. Conversely, the morning shift occupancy was significantly lower,

with only 23 rooms occupied and 11 rooms vacant, yielding a 67.6% utilization rate. This pattern of higher evening usage persisted into the Even Semester. The morning shift occupancy remained identical to the previous semester (23 occupied, 11 vacant, 67.6%). Although the evening shift saw a slight decrease to 27 occupied rooms (and 7 vacant), it still maintained a substantially higher utilization rate of 79.4% compared to the morning shift.

This persistent disparity highlights a fundamental imbalance in resource allocation. The evening shift operates at near capacity, indicating high demand for classes during this time, likely driven by the university's working student demographic. Meanwhile, the morning shift shows a consistent under utilization of available space, with roughly a third of the classrooms remaining vacant.

3.2. State Transition Analysis: Odd Semester to Even Semester

The transition of classroom utilization patterns from the Odd Semester to the Even Semester is fundamental to understanding the dynamics of resource allocation. The raw count of transitions between the four defined states is presented in Table 2.

Table 2. Classroom Transition Patterns

From / To	OV	VO	OO	VV	Outflows
OV	0	0	1	0	1
VO	0	3	2	3	8
OO	0	1	17	4	22
VV	1	0	2	0	3
Total Inflows	1	4	22	7	34

Table 2 shows a significant concentration of classrooms in the OO (occupied in both morning and evening shifts) state during the Odd Semester (22 rooms), indicating it was the most common starting point. The transitions from this state are particularly crucial for analysis. For example, to calculate the transition probabilities from state OO to all other states, the maximum likelihood estimator formula $P_{ij} = \frac{n_{ij}}{n_i}$ is applied, where $n_i = 22$:

$$P_{OO,OV} = \frac{n_{OO,OV}}{n_{OO}} = \frac{0}{22} = 0.000,$$

$$P_{OO,VO} = \frac{n_{OO,VO}}{n_{OO}} = \frac{1}{22} = 0.045,$$

$$P_{OO,OO} = \frac{n_{OO,OO}}{n_{OO}} = \frac{17}{22} = 0.773,$$

$$P_{OO,VV} = \frac{n_{OO,VV}}{n_{OO}} = \frac{4}{22} = 0.182.$$

This calculation is performed for all state transitions, resulting in the transition probability matrix \mathbf{P} :

$$P = \begin{bmatrix} 0.000 & 0.000 & 1.000 & 0.000 \\ 0.000 & 0.375 & 0.250 & 0.375 \\ 0.000 & 0.045 & 0.773 & 0.182 \\ 0.333 & 0.000 & 0.667 & 0.000 \end{bmatrix}.$$

To provide an intuitive visual representation of these transition dynamics, Figure 2 presents a probability flow diagram. The weight on each arrow corresponds to the magnitude of the transition probability between states, clearly illustrating the most and least likely pathways.

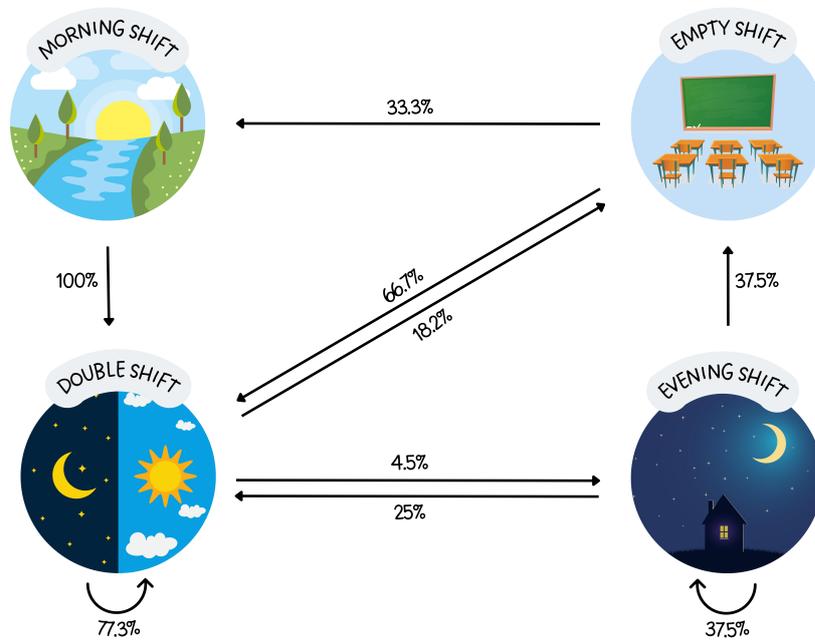


Figure 2. Classroom Utilization Transition Probability Flow Diagram between Semesters

Based on Figure 2, the probability $P_{OO,OO} = 0.773$ is the highest in the system. This indicates that a classroom fully utilized in both shifts in one semester has a 77.3% chance of remaining fully utilized in the next semester. This reflects stable scheduling for high demand rooms. Classrooms vacant in both shifts VV (vacant in both morning and evening shifts) show no stability (0%). Instead, they have a high probability (66.7%) of transitioning to full utilization (OO). This suggests the scheduling system is actively identifying and reallocating underutilized rooms, which is a positive sign for efficiency. Rooms only used in the evening (VO) show the least stable pattern. They have an equal probability of remaining in VO (37.5%) or becoming completely vacant VV (37.5%), with a smaller chance of becoming full OO (25%). This state appears to be a transitional or unstable configuration.

3.3. Steady-State Probability and Long-Term Projection

The transition matrix \mathbf{P} describe the probability of a classroom moving from one state to another in a single semester (a 1-step transition). To understand the long-term behavior, we must analyze the system over multiple semesters. This is achieved by computing the n -step transition probability matrix, denoted as $\mathbf{P}(n)$, which gives the probability of moving from state i to state j in n steps (semester). The n -step transition matrix is found by raising the transition matrix \mathbf{P} to the power of n :

$$\mathbf{P}(n) = \mathbf{P}^n.$$

As we compute \mathbf{P}^n for increasingly larger values of n (e.g., $n = 2, 4, 8, 16, 32, \dots$), we observe a convergence. The rows of the matrix \mathbf{P}^n begin to become identical, and the values in each column stabilize to a fixed value. This convergence indicates that the influence of the initial state on the future state diminishes over time.

$$\mathbf{P}^4 = \begin{bmatrix} 0.0524678130 & 0.0522302850 & 0.7430379160 & 0.1522639860 \\ 0.0515183884 & 0.0620198100 & 0.7282424069 & 0.1582193947 \\ 0.0507039073 & 0.0530230631 & 0.7414537720 & 0.1548192576 \\ 0.0551778293 & 0.0520403801 & 0.7387538990 & 0.1540278916 \end{bmatrix},$$

$$\mathbf{P}^8 = \begin{bmatrix} 0.0515202134 & 0.0533017432 & 0.7404357617 & 0.1547422817 \\ 0.0515531561 & 0.0533847175 & 0.7402888459 & 0.1547732805 \\ 0.0515291798 & 0.0533077630 & 0.7404155949 & 0.1547474623 \\ 0.0515327305 & 0.0532961529 & 0.7404378014 & 0.1547333152 \end{bmatrix}.$$

The system reaches a stochastic equilibrium, meaning the probability of being in any given state becomes constant and independent of the starting point after a sufficiently large number of steps.

$$\lim_{n \rightarrow \infty} \mathbf{P}^n = \mathbf{L} = \begin{bmatrix} 0.0515305454 & 0.0533097586 & 0.7404133135 & 0.1547463825 \\ 0.0515305454 & 0.0533097586 & 0.7404133135 & 0.1547463825 \\ 0.0515305454 & 0.0533097586 & 0.7404133135 & 0.1547463825 \\ 0.0515305454 & 0.0533097586 & 0.7404133135 & 0.1547463825 \end{bmatrix}.$$

This converged matrix, where all rows are identical, is the limiting matrix \mathbf{L} . Each identical row in this limiting matrix is the steady-state probability vector, denoted by $\boldsymbol{\pi}$. The element π_j represents the long run probability that a classroom is in state j , and it is also the proportion of time (or classroom) that will be in that state over a long period.

As shown in Figure 3 and matrix \mathbf{L} , the rows of \mathbf{P}^n are identical. This confirms the system has reached its steady-state. The resulting steady-state vector is:

$$\boldsymbol{\pi} = (0.0515305454, 0.0533097586, 0.7404133135, 0.1547463825).$$

This vector $\boldsymbol{\pi}$ is also the solution to the system of equations defined by:

$$\boldsymbol{\pi}\mathbf{P} = \boldsymbol{\pi} \text{ and } \sum_{i=1}^4 \pi_i = 1.$$

Solving this system of equations algebraically yields the exact same values $\boldsymbol{\pi}$.

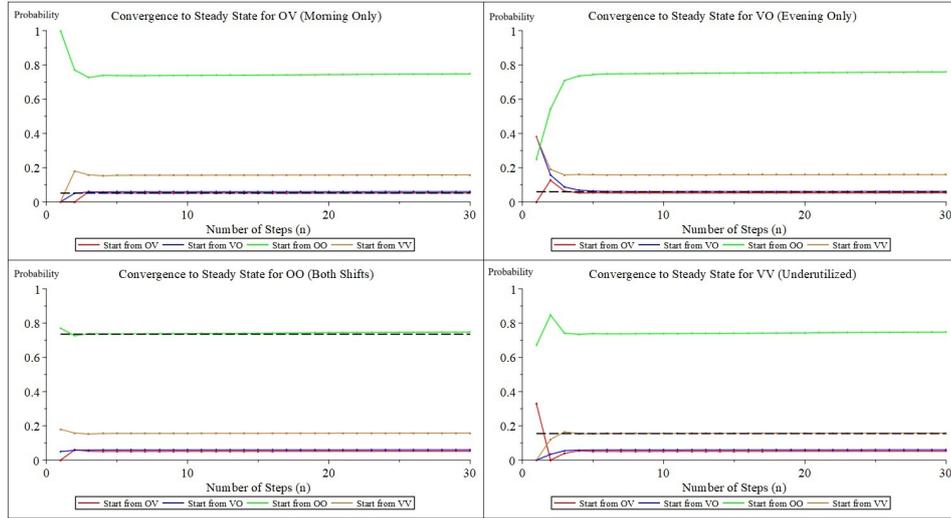


Figure 3. The Long Run Distribution of Classroom Utilization

The interpretation of this result is profound for long-term resource planning. It predicts that, under the current scheduling policies, the long-run distribution of classroom utilization will be 5.15% of classrooms will be scheduled as morning shift only (OV), 5.33% of classrooms will be scheduled as evening shift only (VO), 74.04% of classrooms will be fully utilized in both shifts (OO), and 15.48% of classrooms will remain underutilized in both shifts (VV).

This equilibrium suggests a significant long-term efficiency challenge. While a high proportion (74.04%) of classrooms are consistently fully utilized, a persistent and substantial fraction (15.48%) are predicted to be chronically underutilized. This indicates that the current reactive scheduling, while successful in maximizing use of some rooms, is insufficient to address the structural under utilization of nearly one-sixth of the classroom inventory. Strategic intervention is required to redistribute the scheduling load and reduce this steady-state probability of under utilization.

3.4. Strategic Implications for Resource Management

The steady-state analysis provides a data driven foundation for long term strategic planning. The identified utilization patterns highlight both strengths and critical inefficiencies in the current classroom allocation system. Based on these findings, the following strategic interventions are recommended for ITEBA to optimize resource management, enhance operational efficiency, and achieve significant cost savings.

The 15.48% proportion of unused classrooms indicates the need for a more dynamic space management system. It is recommended to implement an integrated digital reservation system equipped with real time classroom utilization monitoring. This system will provide accurate data for quick decision making in rescheduling and optimizing classroom usage. This approach not only improves efficiency but also reduces operational costs for maintaining unused classrooms.

With 74.04% of classrooms being intensively used across both shifts, policy focus should be on maintaining facility quality. A routine maintenance schedule and class scheduling that avoids classroom overloading are necessary. Scheduling should consider adequate break times for classroom preparation between shifts to maintain the quality of the learning environment.

Classrooms used only during one shift (5.15% morning and 5.33% evening) have potential for increased utilization. This can be achieved by allocating additional academic activities such as seminars, workshops, or thesis guidance during these time slots. Regular evaluation is needed to identify single shift classrooms that can be converted to double shift usage.

Analysis revealed pairs of classrooms with complementary usage patterns across semesters, A302 (full in odd semester, empty in even semester) with A405 (empty in odd semester, full in even semester), and B209 (empty in odd semester, full in even semester) with B211 (full in odd semester, empty in even semester). These classroom pairs can be consolidated by retaining one classroom from each pair (A302 and B211), reducing the active classrooms inventory by approximately 5.9% (from 34 to 32 rooms). This reduction is projected to yield direct and recurring operational cost saving through lower consumption of electricity (for lighting, air conditioning, and audiovisual equipment) and reduced needs for maintenance and cleaning in the two decommissioned rooms. The unused space (A405 and B209) can then be repurposed as discussion rooms, offices, or study spaces, adding new functional value to the campus.

4. Conclusion

This study successfully demonstrates the application of a Markov chain model to analyze and optimize classroom allocation at Batam Institute of Technology (ITEBA) for its shifted lecture system. The research provides a data driven framework for understanding the dynamics of space utilization and offers actionable strategies of long term resource management. The state transition analysis from odd to even semester of the 2024/2025 academic year revealed crucial insights into the short term dynamics of the system.

The constructed transition probability matrix identified strong behavioral patterns, a high probability (77.3%) that fully utilized classrooms remain so, indicating scheduling stability for high demand spaces. Conversely, the analysis uncovered a significant volatility in partially used classrooms and confirmed that severely underutilized classrooms were actively reassigned, showing the system's inherent corrective mechanism, albeit not fully sufficient to eliminate inefficiency.

The steady-state probability and long term projection analysis provided the most critical finding for strategic planning. The resulting steady-state vector π projects that under current policies, 74.04% of classrooms will be consistently full, but a significant 15.48% will remain chronically underutilized in the long run. This projection highlights a persistent structural inefficiency that requires intervention beyond the system's current capabilities.

To address the projected 15.48% under utilization, the study recommends a

multi faceted approach. The implementation of a digital reservation and real time monitoring system to enable dynamic scheduling and data driven decision making. The consolidation of specific classroom pairs that exhibit perfectly complementary usage patterns across semesters. A focused strategy on maintaining the quality of intensively used double shift classrooms while promoting the increased use of single shift slots to better balance the academic load.

Ultimately, the Markov model serves as a powerful diagnostic and predictive tool. For future work, the long-term probabilities and identified utilization patterns generated here can serve as vital input parameters (such as demand forecasts and constraint definitions) for prescriptive optimization models like Linear Programming or Genetic Algorithms, enabling a comprehensive two stage approach to classroom management, strategic forecasting followed by operational scheduling. Furthermore, to enhance the granularity and precision of such models, future implementations should extend beyond binary occupancy data. The proposed digital monitoring system should record actual usage hours and intensity per-room per-shift. This data refinement would enable more nuanced, intensity-based Markov analysis and provide higher-fidelity inputs for optimization algorithms, ultimately leading to more accurate space utilization planning and resource allocation.

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