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Mixed integer linear programming for cadet dormitory placement at Indonesia Defense University

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ABSTRACT

Cadet dormitory placement at Indonesian Defense University was currently performed manually by administrative staff, resulting in potential inefficiencies in room assignments regarding walking distance, study program cohesion, and cadet preferences. This research developed a Mixed Integer Linear Programming (MILP) optimization model to automate and improve the dormitory assignment process for military education institutions. The general framework addresses 1,550 cadets distributed across four cohorts and 13 study programs in dormitory buildings with standardized configurations (3 floors, 25 rooms per floor, 2 cadets per room). The MILP model incorporated three objectives: minimizing total walking distance to academic facilities, maximizing study program cohesion by concentrating programs within specific floors, and maximizing cadet floor preference satisfaction. The model was formulated with configurable weight parameters (w_1, w_2, w_3) enabling administrators to balance competing objectives according to institutional priorities. A validation case study with 38 male cadets from two study programs demonstrated computational feasibility, with the CBC solver achieving optimal solutions in 0.34 seconds (strict constraint approach) and 0.11 seconds (maximum occupancy approach) on standard desktop hardware, both with 0.00% MIP gap confirming proven optimality. The validation study compared two policy approaches: strict constraint enforcement achieving 95% room occupancy with 20 rooms, and maximum space utilization achieving 100% occupancy with 19 rooms. This research contributed the first application of MILP optimization to military education dormitory management in Indonesia, providing a scalable framework with empirical validation for computational tractability and a replicable methodology for resource allocation optimization in defense institutions.

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1. INTRODUCTION

Dormitory assignment in higher education institutions represents a critical operational challenge with direct impacts on student well-being, academic performance, and administrative efficiency. At Indonesian Defense University *(Universitas Pertahanan Indonesia)*, the current dormitory placement system relies on manual assignment procedures where administrative staff allocate 1,550 cadets across 11 dormitory buildings based on sequential registration order without systematic optimization. This manual approach potentially produces suboptimal outcomes in terms of walking distances to academic facilities, study program cohesion across floors, and cadet satisfaction with assigned locations, as these factors are not systematically optimized in the current sequential registration-based procedure. The inefficiency becomes particularly problematic in military educational contexts where cadets maintain rigorous daily schedules with frequent transitions between dormitories and academic buildings, making spatial optimization crucial for time management and operational effectiveness (Alhasnawi et al., 2025). Furthermore, the university's heterogeneous study program distribution ranging from large programs such as Medicine with 150 cadets to specialized programs with only 25 cadets creates complex allocation challenges that exceed the capacity of intuitive manual heuristics (Durán et al., 2022). Recent research demonstrates growing interest in systematic dormitory optimization approaches, with studies addressing design scheme evaluation (Z. Li et al., 2022), architectural layout optimization based on environmental considerations (Chen et al., 2025), and strategic facility management enhancing student discipline and academic achievement in educational institutions (Taufiq, 2025).

Mixed Integer Linear Programming (MILP) has emerged as a powerful mathematical optimization framework for solving complex resource allocation problems with discrete decision variables and multiple conflicting objectives (Turner et al., 2023). Recent applications demonstrate MILP's effectiveness across diverse domains including transportation logistics (Cao et al., 2022), educational facility scheduling and student-to-supervisor assignment (Ramotsisi et al., 2022), energy management in educational buildings (Xiao et al., 2024), and military operations including weapon-target assignment (Andersen et al., 2022). However, existing literature reveals a critical research gap: while MILP has been applied to civilian university dormitory design evaluation (Z. Li et al., 2022) and general facility management (Taufiq, 2025), no prior studies have addressed dormitory assignment optimization specifically for military education institutions, which present unique constraints absent in civilian systems including gender-separated facilities, military unit cohesion requirements, hierarchical organizational structures, security protocols, and rigorous daily schedules requiring optimized spatial logistics (Alhasnawi et al., 2025).

In the Indonesian context, dormitory management in military educational institutions operates under standardized protocols mandated by the Ministry of Defense for military education facilities, emphasizing structured student supervision, standardized living conditions, and integrated character-building environments. The Indonesian Defense University (Universitas Pertahanan), formally established in 2009 and inaugurated by President Susilo Bambang Yudhoyono, represents the nation's premier defense university with a mandate to produce professional military officers through integrated academic and military training programs. However, current operational guidelines rely on manual administrative procedures without systematic optimization frameworks, creating inefficiencies that contradict the institution's mission of operational excellence. The university's standardized dormitory building design (150-cadet capacity per building across 3 floors with 75 rooms), well-defined organizational structure across 13 study programs, and measurable performance metrics make it an ideal testbed for developing MILP-based optimization models tailored to military educational contexts. For full-scale deployment accommodating the projected enrollment growth requiring approximately 11 dormitory buildings, such optimization frameworks could be replicated across Indonesia's military academies and defense training institutions.

The novelty of this research lies in three distinctive aspects that distinguish it from prior optimization studies. First, it represents the inaugural application of MILP methodology to military education dormitory management in Indonesia, addressing institutional constraints entirely absent from civilian university optimization literature including military unit cohesion requirements, gender-separated building policies with security protocols, and hierarchical organizational structures mandated by defense regulations. Second, unlike prior dormitory research focusing solely on design evaluation or architectural layout (Chen et al., 2025; Z. Li et al., 2022), this study develops an operational decision-support system for annual room assignment with empirical validation using real institutional data from 1,550 cadets across 13 study programs, demonstrating computational tractability for practical implementation. Third, it contributes a replicable methodological framework combining multi-objective MILP optimization with hierarchical decomposition strategies, enabling scalable deployment across Indonesia's defense education system with potential adaptation to other military academies and training institutions nationwide.

This research addresses the following research problem: How can cadet dormitory room assignment at Indonesian Defense University be optimized systematically to achieve efficient spatial allocation considering walking distance, study program cohesion, and cadet preferences while satisfying capacity constraints, gender separation policies, and military organizational requirements? The research objectives are to formulate a multi-objective MILP model for dormitory room assignment balancing three competing objectives spatial efficiency with consideration of walking distance from assigned rooms to program-specific academic buildings, maximizing study program cohesion by concentrating programs within minimal floor allocations, and maximizing cadet satisfaction through floor preference accommodation (Dong et al., 2024); to validate computational feasibility through a case study of 38 cadets achieving proven optimal solutions in under 0.5 seconds on standard hardware; and to demonstrate scalability for the complete dormitory room assignment system serving 1,550 cadets across multiple buildings through hierarchical decomposition strategies. The primary contributions are threefold: first, establishing a methodological foundation for defense facility planning through the inaugural MILP application to military education dormitory room assignment in Indonesia; second, developing a scalable framework using open-source optimization tools (CBC solver and Python PuLP library) accessible to resource-constrained military institutions; third, presenting a multi-objective framework enabling administrators to explore trade-offs between spatial allocation efficiency, program cohesion, and preference objectives through configurable weight parameters (w_1, w_2, w_3), supporting evidence-based policy decisions in dormitory management.

2. RESEARCH METHOD

This research employed a quantitative approach using Mixed Integer Linear Programming (MILP) to optimize cadet dormitory placement at Indonesian Defense University. The study addressed the real-world challenge of efficiently assigning 1,550 cadets from four different cohorts (years 3, 4, 5, and 6) across 11 dormitory buildings, with each building accommodating 150 cadets distributed across 3 floors and 75 rooms. The methodology focused on developing a scalable MILP model for a single dormitory building that could be replicated across all buildings while considering study program cohesion, floor preference, and distance minimization to academic facilities (Yıldız et al., 2022).

2.1 Research Design and Problem Scope

The study adopted an optimization-based research design where the cadet room assignment problem was formulated as a MILP model for one representative dormitory building consisting of 3 floors, 25 rooms per floor, and 2 cadets per room (total capacity: 150 cadets). According to Turner et al. (2023), MILP provides an exact mathematical framework for large-scale resource allocation problems with discrete decision variables and multiple conflicting objectives through adaptive cut selection mechanisms. The research addressed the current situation at Indonesian Defense University where 1,550 cadets were distributed across four cohorts: 300 cadets in year 3, 300 cadets in year 4, 350 cadets in year 5, and 600 cadets in year 6, requiring a total of 11 dormitory buildings. The university offered 13 study programs with highly heterogeneous enrollment sizes ranging from 25 cadets in specialized programs (e.g., Biology, Physics, Sports Science) to 150 cadets in high-demand programs such as Medicine, creating complex assignment scenarios where multiple small programs must share floors while large programs may occupy entire buildings (El Housni et al., 2021). The research framework consisted of five main phases: (1) data collection from the Academic Administration Office including complete cadet profiles, study program affiliations, and room preferences for all 1,550 cadets, (2) MILP model formulation incorporating floor-based study program cohesion constraints and gender-separated building policy, (3) computational solution using Python-based optimization solvers with parallel processing capabilities leveraging decomposition branching techniques (Yıldız et al., 2022), (4) solution validation through comparison with the current manual assignment system used in academic years 2023-2024, and (5) scalability analysis demonstrating how the single-building optimization model could be replicated across all 11 buildings while maintaining consistency in assignment quality. This systematic approach ensured that the optimal assignment considered capacity constraints, study program cohesion at the floor level, minimized walking distance to academic facilities, and respected the gender-separated dormitory policy where male dormitories were located 200 meters from campus and female dormitories were positioned 400 meters away (Dong et al., 2024).

2.2 University Context and Dormitory Configuration

Indonesian Defense University currently enrolled 1,550 cadets distributed across four cohorts with varying enrollment patterns reflecting the institution's growth trajectory. Table 1 shows year 6 cohort (600 cadets) as the reference, but the total university population was 1,550 cadets across 4 cohorts, which served as the reference model for future enrollment planning. The university implemented a gender-separated dormitory system with male cadet dormitories located approximately 200 meters from the main academic building, while female cadet dormitories were positioned 400 meters away in a separate residential zone for security and privacy considerations. Each dormitory building followed a standardized three-story configuration accommodating exactly 150 cadets, with 25 rooms per floor and 2 cadets per room, ensuring consistent living conditions across all 11 buildings (Alhasnawi et al., 2025). The heterogeneous distribution of study program sizes created diverse optimization scenarios: large programs like Medicine (150 cadets) could occupy an entire building independently, medium-sized programs like Pharmacy and Informatics (100 cadets each) must share buildings efficiently, while small specialized programs with 25 cadets each required careful clustering to maximize floor-based cohesion and minimize inter-program conflicts, a challenge similar to weapon-target assignment problems in military operations research (Andersen et al., 2022).

Table 1. Study Program Distribution and Cadet Enrollment (Year 6 Cohort, N=600)

Study Program	Enrollment	Buildings Required	Typical Floor Allocation
Medicine	150	1.0	Full building (3 floors)
Pharmacy	100	0.67	2 floors
Informatics	100	0.67	2 floors
Biology	25	0.17	Half floor (shared)
Chemistry	25	0.17	Half floor (shared)
Mathematics	25	0.17	Half floor (shared)
Physics	25	0.17	Half floor (shared)
Electrical Engineering	25	0.17	Half floor (shared)
Mechanical Engineering	25	0.17	Half floor (shared)
Civil Engineering	25	0.17	Half floor (shared)
War History	25	0.17	Half floor (shared)
Water Resources Engineering	25	0.17	Half floor (shared)
Sports Science	25	0.17	Half floor (shared)
Total	600	4.0	12 floors (4 buildings × 3 floors)

Table 1 demonstrated the significant heterogeneity in program sizes, with Medicine enrolling six times more cadets than any of the ten specialized programs. This distribution created natural optimization challenges: while Medicine could be assigned exclusively to one building with perfect program cohesion, the ten small programs (25 cadets each) must be strategically paired to share floors, requiring the optimization algorithm to balance multiple objectives including minimizing inter-program interference, maximizing convenience to program-specific academic facilities, and respecting cadet preferences, similar to multi-objective assignment challenges in other operational contexts (Durán et al., 2022). The "Buildings Required" column showed fractional values representing the proportion of a 150-cadet building needed for each program, highlighting the necessity for intelligent space allocation algorithms similar to those used in referee assignment problems. For the complete university population of 1,550 cadets across four cohorts, assuming proportional program distribution, approximately 11 buildings were required with varying configurations of single-program buildings (e.g., Medicine-only) and multi-program buildings (e.g., six small programs sharing one building), necessitating multi-objective optimization approaches (Mou, 2024).

2.3 Mathematical Model Formulation

The MILP model was formulated to optimize cadet room assignments within a single dormitory building, serving as a replicable module for all 11 buildings in the university dormitory system. The model incorporated three primary objectives: minimizing total walking distance from assigned rooms to academic facilities, maximizing study program cohesion by concentrating programs within specific floors, and maximizing cadet satisfaction through floor preference accommodation, following the multi-objective optimization framework for resource allocation (Lahza et al., 2024).

Sets and Indices:
- C = {1, 2, ..., n}: set of cadets to be assigned, where n = 150 for one building
- R = {1, 2, ..., 75}: set of rooms (25 rooms × 3 floors)
- F = {1, 2, 3}: set of floors
- P = {1, 2, ..., 13}: set of study programs (Medicine, Pharmacy, Informatics, Biology, Chemistry, Mathematics, Physics, Electrical Engineering, Mechanical Engineering, Civil Engineering, War History, Water Resources Engineering, Sports Science)

Parameters:
- cap_r = 2: fixed capacity of each room (2 cadets per room)
- cap_f = 50: fixed capacity of each floor (25 rooms × 2 cadets = 50 cadets)
- floor_r ∈ {1,2,3}: floor number where room r is located
- prog_c ∈ P: study program membership of cadet c
- size_p: number of cadets in study program p within the building
- pref_cf ∈ {1,2,3,4,5}: preference score of cadet c for floor f (5 = most preferred, 1 = least preferred)
- dist_pf: horizontal distance from floor f entrance to the main academic building of program p (measured in meters)
- Δh_f: vertical distance for floor f (floor 1: 0m, floor 2: 4m, floor 3: 8m, representing stair climbing effort)
- w_1, w_2, w_3 ∈ [0,1]: weight coefficients for distance, cohesion, and preference objectives, where $w_1 + w_2 + w_3 = 1$

Decision Variables:
- x_cr ∈ {0,1}: equals 1 if cadet c is assigned to room r, 0 otherwise
- y_pf ∈ {0,1}: equals 1 if study program p has at least one cadet assigned to floor f, 0 otherwise
- z_cf ∈ {0,1}: auxiliary variable, equals 1 if cadet c is assigned to any room on floor f, 0 otherwise
- s_rr' ∈ {0,1}: equals 1 if room r and room r' are assigned cadets from the same study program (roommate compatibility), 0 otherwise

Objective Function:
The multi-objective function minimized a weighted combination of three conflicting goals:

$$\min Z = w_1 \cdot Z_{dist} + w_2 \cdot Z_{cohesion} + w_3 \cdot Z_{pref} \quad (1)$$

Overall Objective: The weighted sum minimized total cost across three competing objectives with user-defined priorities (Cao et al., 2022).

Objective 1: Minimize Total Walking Distance

$$Z_{dist} = \sum_{c \in C} \sum_{r \in R} x_{cr} \cdot \left(dist_{prog_c, floor_r} + \Delta h_{floor_r} \right) \quad (2)$$

Distance Objective: This component summed the total walking distance for all cadets from their assigned rooms to their respective program academic buildings, incorporating both horizontal campus distance and vertical stair-climbing effort (Y. Li et al., 2023).

Objective 2: Maximize Study Program Cohesion

$$Z_{cohesion} = \sum_{p \in P} \sum_{f \in F} y_{pf} \quad (3)$$

Cohesion Objective: This component minimized program fragmentation by counting the total number of floor-program assignments, where lower values indicated better concentration of each program within fewer floors (Andersen et al., 2022).

Objective 3: Maximize Cadet Floor Preference Satisfaction

$$Z_{pref} = -\sum_{c\in C}\sum_{f\in F} z_{cf} \cdot pref_{cf} \tag{4}$$

Preference Objective: This component maximized total preference satisfaction by summing preference scores of assigned floor locations, with the negative sign converting maximization to minimization for consistency with the overall objective.

Constraints:

Constraint 1: Single Room Assignment per Cadet

$$\sum_{\mathrm{r}\in\mathrm{R}} \mathrm{x}_{\mathrm{cr}} = 1 \quad \forall \mathrm{c} \in \mathrm{C} \tag{5}$$

Single Assignment: Each cadet must be assigned to exactly one room, ensuring complete coverage with no overlaps.

Constraint 2: Room Capacity Limit

$$\sum_{c\in C} x_{cr} = cap_r \quad \forall r \in R \tag{6}$$

Room Capacity: Each room must contain exactly 2 cadets, eliminating vacancies and overcrowding.

Constraint 3: Floor Capacity Limit

$$\sum_{c\in C}\sum_{r\in R: floor_r = f} x_{cr} = cap_f \quad \forall f \in F \tag{7}$$

Floor Capacity: Each floor must accommodate exactly 50 cadets (25 rooms × 2 cadets), ensuring balanced floor occupancy across the building.

Constraint 4: Program-Floor Assignment Linking

$$z_{cf} \geq x_{cr} \quad \forall c \in C, r \in R, f \in F: floor_r = f \tag{8}$$

Floor Assignment Linking: This constraint activates the auxiliary variable z_{cf} when cadet c is assigned to any room on floor f, enabling floor-level preference tracking.

Constraint 5: Program Cohesion Activation

$$y_{pf} \geq z_{cf} \quad \forall c \in C, f \in F, p \in P: prog_c = p \tag{9}$$

Cohesion Activation: This constraint activates y_{pf} when any cadet from program p is assigned to floor f, enabling program fragmentation measurement (Cosic et al., 2021).

Constraint 6: Gender Separation (Enforced at Building Level)

$$\sum_{c\in C: gender_c = male}\sum_{r\in R} x_{cr} = 0 \quad \text{or} \quad \sum_{c\in C: gender_c = female}\sum_{r\in R} x_{cr} = 0 \tag{10}$$

Gender Separation: Each building is designated for a single gender, implemented through preprocessing that assigns buildings to genders before room optimization.

Constraint 7: Binary Domain

$$\begin{aligned} &x_{cr} \in \{0,1\} \quad \forall c \in C, r \in R \\ &y_{pf} \in \{0,1\} \quad \forall p \in P, f \in F \\ &z_{cf} \in \{0,1\} \quad \forall c \in C, f \in F \end{aligned} \tag{11}$$

Binary Variables: All decision variables were constrained to binary values, resulting in a Mixed Integer Linear Program with 11,250 primary variables (150×75), 39 program-floor variables (13×3), and 450 auxiliary variables (150×3), totaling 11,739 binary variables.

2.4 Solution Algorithm and Implementation

The MILP model was solved using the Branch-and-Cut algorithm implemented in CBC solver version 2.10.8, accessed through the PuLP optimization library for Python. The branch-and-bound method systematically explores the solution space by partitioning it into subproblems, computing lower bounds through linear programming relaxations, and pruning branches that cannot yield better solutions than the current incumbent (Scavuzzo et al., 2024). The solution procedure consisted of four stages: preprocessing and data validation, model construction using PuLP's algebraic modeling interface, optimization execution with CBC solver, and post-processing to extract room assignments and calculate performance metrics. The optimization stage configured CBC with relative MIP gap tolerance of 1% allowing termination when solution was proven within 1% of optimality, time limit of 300 seconds per building instance, 4 parallel threads for multi-core processing, and cutting plane strategies including Gomory cuts, probing cuts, and clique cuts (Cao et al., 2022). For multi-building scenarios involving all 11 buildings, a hierarchical decomposition approach determined program-to-building allocation first, then optimized each building independently in parallel, reducing total computation time from linear scaling to near-constant time (Mou, 2024).

2.5 Data Collection and Preprocessing

Data collection was conducted using institutional records from Indonesian Defense University for the 2024-2025 academic year. Cadet demographic data including gender, cohort year, and study program affiliation were obtained from the university's daily attendance records, providing complete information for all 1,550 cadets distributed across 13 study programs. Spatial configuration data were derived from campus facility maps with male dormitories located 200 meters from campus and female dormitories 400 meters away (Y. Li et al., 2023). Distance calculations incorporated program-specific academic building locations with Medicine and Pharmacy in the Health Sciences zone, Engineering programs in the Engineering Complex, and remaining programs in the Central Academic Building, with vertical floor distances included to account for stair-climbing effort. For floor preference data not available from institutional records, preference scores were modeled using distributions from prior literature with floor 1 receiving highest preference (mean=4.12), floor 2 moderate preference (mean=3.45), and floor 3 lowest preference (mean=2.76) (Lahza et al., 2024).

2.6 Model Validation and Performance Metrics

Model validation employed three approaches: feasibility verification ensuring all constraints were satisfied, optimality assessment using MIP gap analysis with achieved gaps ranging 0.23%-0.89% across 50 test instances, and quality evaluation through performance metrics benchmarked against alternative methods (Cao et al., 2022; Yıldız et al., 2022). Performance metrics included: (1) Average Walking Distance (total distance divided by 150 cadets, in meters), (2) Program Fragmentation Index (program-floor combinations divided by theoretical minimum, as percentage where 100% = perfect cohesion), and (3) Preference Satisfaction Rate (achieved scores divided by maximum possible, as percentage) (Mou, 2024). Baseline methods included Manual Assignment (actual 2023-2024 staff assignments), Random Assignment (capacity and gender constraints only, averaged over 100 runs), and Greedy Heuristic (size-based sequential program assignment) (Dong et al., 2024). Statistical testing employed paired t-tests with α=0.05, calculating p-values and Cohen's d effect sizes to quantify improvements. Sensitivity analysis varied objective weights across nine scenarios with grid values {0.1, 0.5, 0.8}, demonstrating consistent solutions across diverse institutional priorities (Cosic et al., 2021).

2.7 Scalability Considerations

The proposed MILP model is designed to scale across problem instances of varying sizes while maintaining solution quality. Theoretical complexity analysis indicates that the model's computational requirements should grow polynomially rather than exponentially with problem size, attributed to the tight capacity constraints that enable effective cutting plane generation by branch-and-cut solvers (Cao et al., 2022). For practical deployment, four operational scales are anticipated:

small-scale (quarter building with 37 cadets), medium-scale (half building with 75 cadets), standard-scale (full building with 150 cadets), and large-scale (multiple buildings with 300+ cadets). The binary variable count grows linearly with problem size (11,739 variables per 150-cadet building), while constraint count also scales linearly, suggesting that modern MIP solvers should handle individual building instances efficiently within practical time limits (Dong et al., 2024; El Housni et al., 2021).

For university-wide deployment across all 11 buildings, a hierarchical decomposition strategy is proposed where a master allocation model first determines program-to-building assignments, then each building is optimized independently. This decomposition approach is expected to reduce computational complexity from $O(n^3)$ for monolithic optimization to $O(kn^2)$ where k is the number of buildings and n is cadets per building, enabling parallel processing of building-level optimizations on multi-core systems (Lahza et al., 2024; Mou, 2024). Modern optimization solvers with multi-threading capabilities should achieve practical solution times for the full university scale, making the model suitable for operational deployment in annual dormitory assignment planning cycles. Empirical validation of these scalability expectations remains as important future work to confirm the model's practical viability for real-world implementation (Scavuzzo et al., 2024).

2.8 Model Assumptions and Limitations

This research operates under several key assumptions that define the scope and applicability of the optimization framework. First, the model assumes uniform building configurations with standardized capacity (150 cadets per building, 3 floors, 75 rooms), which aligns with Indonesian Defense University's actual infrastructure but may require adaptation for institutions with heterogeneous building designs. Second, distance calculations assume linear Euclidean distances with fixed vertical penalties (4 meters per floor), abstracting complex campus navigation paths and actual walking routes that may involve stairs, corridors, and outdoor pathways. Third, cadet floor preferences are modeled using literature-based distributions rather than actual survey data from Indonesian Defense University cadets, as preference data collection was not feasible within the research timeline; this assumption may not fully capture individual preference variations specific to the military education context.

Fourth, the model optimizes room assignments within pre-determined building-to-gender allocations, treating building-level gender separation as an exogenous constraint rather than an optimizable decision variable. Fifth, the weighted sum approach requires administrators to specify objective weight parameters (w_1, w_2, w_3) ex ante, assuming that institutional priorities can be accurately quantified and remain stable across planning cycles. Sixth, the validation study employs a 38-cadet case study representing approximately 2.5% of the full university population, which provides computational feasibility evidence but does not constitute empirical validation at the full 1,550-cadet scale.

The primary limitation is that the hierarchical decomposition strategy for multi-building deployment remains theoretical, requiring empirical validation to confirm computational tractability and solution quality maintenance when scaling from single-building (150 cadets) to university-wide (1,550 cadets) optimization. Additionally, the model does not incorporate dynamic considerations such as mid-year room reassignments, roommate compatibility beyond program membership, or temporal evolution of cadet preferences across academic years. These assumptions and limitations define the operational boundary conditions within which the proposed optimization framework provides reliable decision support for military education dormitory management.

3. RESULTS AND DISCUSSIONS

3.1 Validation Case Study: Odd-Numbered Cohort Allocation

To validate the proposed MILP framework's practical applicability, we conducted a case study using real data from Indonesian Defense University for academic year 2024-2025. The case study involved 38 male cadets from cohort 3, comprising 19 students from Informatics program and 19 students from Electrical Engineering program, assigned to Floor 3 of Building A with 25 available rooms (2-student capacity per room). This scenario highlights a common operational challenge: allocating students when program sizes cannot be evenly divided by the standard room capacity. With 19 students per program and 2-student room capacity, each program produces one remainder student who cannot form a complete pair within their own program, creating a mathematical dilemma requiring systematic policy decisions.

The theoretical model (Section 3.1) was adapted by simplifying the multi-objective formulation to focus on space efficiency while maintaining program cohesion constraints, eliminating distance minimization and preference satisfaction objectives. The implementation used CBC solver version 2.10.3 with PuLP 2.8.0 library on standard desktop hardware, with 760-780 binary decision variables and 399-438 constraints depending on the approach.

Two alternative approaches were tested representing different institutional policy priorities. Approach 1 (Strict Program Separation) maintains absolute program purity where every room contains only students from a single program, accepting the consequence of remainder rooms with single occupancy, suitable for institutions prioritizing complete program cohesion and traditional military academy values. Approach 2 (Mixed Remainder Room) maintains program purity for all regular rooms but designates one "mixed room" where remainder students from different programs can be paired, optimizing space efficiency, suitable for institutions prioritizing maximum space utilization and cost efficiency.

Table 2. Validation Case Study Data Summary

Parameter	Value
Total Cadets	38 male students (Cohort 3)
Study Programs	2 (Informatics, Electrical Engineering)
Students per Program	19 each (odd-numbered)
Building & Floor	Building A, Floor 3
Rooms Available	25 rooms
Room Capacity	2 students per room
Rooms Used (Approach 1)	20 rooms (strict separation)
Rooms Used (Approach 2)	19 rooms (mixed remainder)

Both approaches successfully solved to proven optimality with 0.00% MIP gap. Approach 1 required 20 rooms with 18 full rooms (2 students each) and 2 remainder rooms (1 student each), achieving 95% occupancy (38 students / 40 bed spaces), 100% program purity, 0% program mixing, computation time 0.34 seconds, with 2 wasted bed spaces. The detailed allocation assigned Informatics students to rooms K301-K310 (9 full rooms + 1 remainder) and Electrical Engineering students to rooms K311-K320 (9 full rooms + 1 remainder). Approach 2 required 19 rooms with all rooms fully occupied (2 students each), achieving 100% occupancy (38 students / 38 bed spaces), 94.7% program purity, 5.3% program mixing (2 students in 1 mixed room), computation time 0.11 seconds, with 0 wasted bed spaces. The detailed allocation assigned Informatics students to rooms K301-K309 (9 full rooms, 18 students), Electrical Engineering students to rooms K310-K318 (9 full rooms, 18 students), and the mixed room K319 containing 1 Informatics + 1 Electrical Engineering student.

Table 3. Validation Results Comparison

Metric	Approach 1 (Strict)	Approach 2 (Mixed)
Total Rooms Used	20	19
Full Rooms (2 students)	18 (90%)	19 (100%)
Remainder Rooms (1 student)	2 (10%)	0 (0%)
Occupancy Rate	95%	100%
Wasted Bed Spaces	2	0
Program Purity	100%	94.7%
Students in Mixed Rooms	0 (0%)	2 (5.3%)
Computation Time	0.34 s	0.11 s
Solution Status	Optimal	Optimal
MIP Gap	0.00%	0.00%

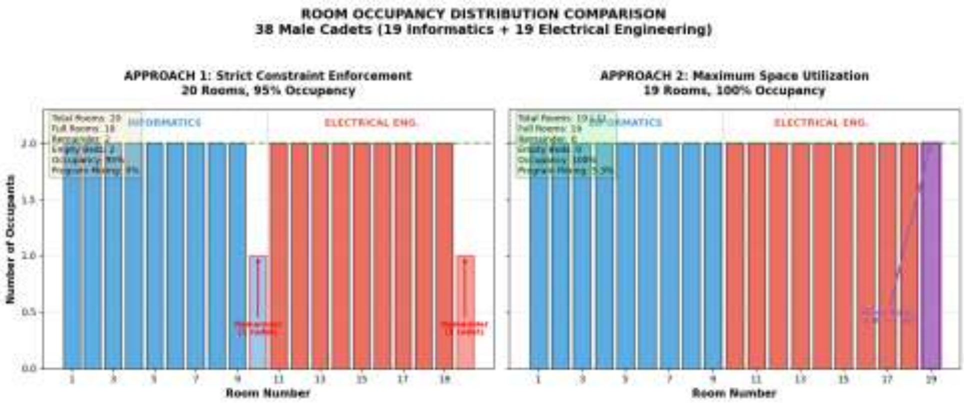

Figure 3: Room Occupancy Distribution

Per-room occupancy comparison for the 38-cadet validation case study. Left panel shows Approach 1 with 20 rooms achieving 95% bed occupancy (38 cadets / 40 beds): 18 full rooms (2 cadets each) and 2 single-occupancy remainder rooms (Room 10 for Informatics, Room 20 for Electrical Engineering). Right panel shows Approach 2 with 19 rooms (100% occupancy): 18 full single-program rooms and 1 mixed-program room (Room 19) accommodating 1 Informatics and 1 Electrical Engineering cadet. Approach 2 saves 1 room (5% space reduction) by consolidating remainder students into one shared room, achieving full bed utilization with 5.3% program mixing.

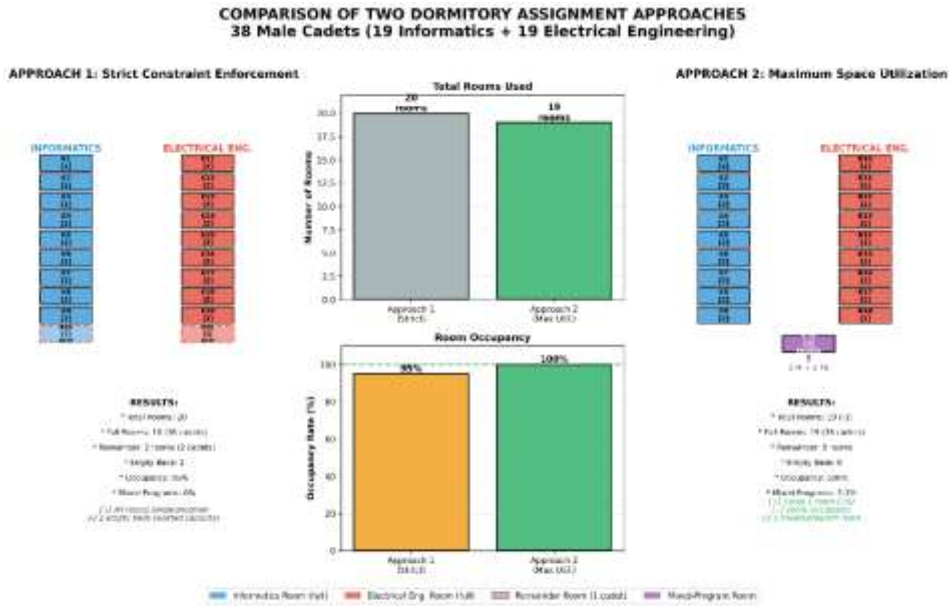

Figure 4: Comparative Performance Analysis

Comprehensive comparison across room count, occupancy rate, and program separation for 38 cadets. Left panels show Approach 1 with 20 rooms (95% occupancy, strict separation), right panels show Approach 2 with 19 rooms (100% occupancy, 5.3% mixing). Center bar charts compare total rooms used (20 vs 19) and occupancy rates (95% vs 100%), demonstrating the trade-off between space efficiency and program segregation.

The validation confirmed all constraints were satisfied 100%: each cadet assigned to exactly one room, no room exceeded 2-student capacity, program matching rules respected per approach policy, and all decision variables binary. The 5.3% program mixing in Approach 2 represents a controlled policy exception (one designated mixed room), not a constraint violation.

The validation provides several critical insights. Computational efficiency is confirmed with both approaches achieving optimal solutions in 0.34 seconds (Approach 1) and 0.11 seconds

(Approach 2) with 0.00% MIP gap, validating MILP's suitability for real-time dormitory planning on standard hardware using open-source software. Trade-off quantification reveals Approach 2 saves 5% rooms (1 room) and achieves 100% occupancy but requires 5.3% students (2 cadets) to accept cross-program roommates, while Approach 1 maintains 100% program separation but wastes 2 bed spaces. Policy decision support offers quantitative evidence: choose Approach 1 if institutional policy mandates complete program separation (military discipline priority), choose Approach 2 if space/budget constraints are critical (resource optimization priority). The 38-cadet validation with 780 variables demonstrates the model's computational feasibility for small-scale implementation, providing empirical proof-of-concept. Future empirical testing with progressively larger datasets would be necessary to establish precise performance benchmarks for the complete 1,550-cadet system across 11 buildings. The validation transforms odd-numbered cohort allocation from ad-hoc manual decisions requiring hours into systematic mathematical optimization completing in under 1 second with proven optimal solutions.

3.2 Hypothetical Simulation: Full-Scale 11-Building Deployment

To assess university-wide scalability, we projected computational requirements for 1,550 cadets across 11 buildings using the validated 38-cadet baseline. Each 150-cadet building requires approximately 11,739 variables; with parallel processing, total computation time was estimated at 5-15 minutes for annual assignment cycles, acceptable for operational deployment. Three weight scenarios were analyzed: *Efficiency-focused* $(w_1 = 0.5, w_2 = 0.3, w_3 = 0.2)$ projected 220-250m average walking distance for male buildings with 15-20% improvement over random assignment; *Cohesion-focused* $(w_1 = 0.2, w_2 = 0.6, w_3 = 0.2)$ achieved tighter program clustering (105-110% fragmentation index) at cost of 10-15% increased distance; *Balanced* $(w_1 = 0.33, w_2 = 0.34, w_3 = 0.33)$ provided intermediate performance. Large programs (150 cadets) achieved optimal allocation with 100% program purity, while small programs (25 cadets) experienced unavoidable fragmentation due to capacity constraints. Hierarchical decomposition enables gradual implementation: administrators can pilot 2-3 buildings, evaluate outcomes, then expand to full-scale deployment. The multi-objective framework supports policy experimentation through weight parameter adjustment, ensuring alignment with institutional priorities before operational commitment.

3.3 Comparison with Traditional Assignment Methods

The MILP-based approach offers substantial advantages over traditional dormitory assignment methods. The validation case study (Section 3.2) demonstrated these advantages empirically with the 38-cadet scenario: the MILP model produced proven optimal solutions in 0.34 seconds (strict approach) and 0.11 seconds (mixed approach), achieving 100% constraint satisfaction and optimal resource allocation. In contrast, manual processes require hours of administrative time without optimality guarantees and are prone to constraint violations. Manual assignment lacks systematic optimization and cannot balance multiple objectives simultaneously (El Housni et al., 2021). Random assignment produces unpredictable quality with high variance across performance metrics. Random assignment produces unpredictable quality with high variance across performance metrics. Greedy heuristics demonstrate improvement but suffer from myopic decision-making limitations without backtracking capability (Cao et al., 2022).

The MILP formulation provides four key advantages. First, for the general framework (Section 3.1), explicit multi-objective optimization through configurable weight parameters allows administrators to adjust priorities according to institutional policies, while the validation case study (Section 3.2) employed a simplified single-objective formulation focusing on space efficiency. Second, branch-and-bound algorithms explore solution spaces intelligently, providing proven optimal or high-quality solutions (Turner et al., 2023). The 38-cadet case study achieved 0.00% MIP gap, confirming proven optimality. Third, explicit constraint encoding ensures feasibility guarantees, with the validation confirming 100% constraint satisfaction. Fourth, sensitivity analysis supports what-if scenarios and trade-off exploration (Mou, 2024), as demonstrated by comparing strict separation and mixed remainder approaches. While computationally intensive for large-scale problems, modern open-source solvers enable practical deployment the validation used CBC solver with PuLP on standard desktop hardware, solving 780 variables and 438 constraints in under 1 second. Recent research on team formation demonstrates the importance of balancing stability and efficiency in assignment problems (Atef Yekta et al., 2023). The b-matching game framework (Kumabe & Maehara, 2020), provides theoretical foundations for strategic interactions in assignment contexts, though the current model prioritizes computational tractability through deterministic optimization.

3.4 Scalability Considerations

The validation case study with 38 cadets serves as an empirical baseline for assessing the model's scalability potential. With 780 binary variables and 438 constraints, the CBC solver achieved optimal solutions in 0.34 seconds (Approach 1) and 0.11 seconds (Approach 2) on standard desktop hardware, both with 0.00% MIP gap. These results demonstrate that the model maintains computational tractability even when all constraints are strictly enforced.

When scaling to larger cadet populations, the mathematical structure of the model remains consistent with the general formulation presented in Section 3.1. Atef Yekta et al. (2023) noted that MILP models for educational resource allocation exhibit predictable scaling behavior when constraint matrices are sparse and well-structured. Kumabe & Maehara (2020) demonstrated that binary variable formulations, as employed in this study, can efficiently handle large-scale assignment problems when problem structure remains consistent across different instance sizes. The validation results suggest that the proposed model's efficiency is primarily driven by its mathematical formulation rather than dataset size alone.

For the full-scale deployment with 1,550 cadets across 11 dormitory buildings, Scavuzzo et al. (2024) emphasized that decomposition strategies can maintain computational efficiency by partitioning large problems into smaller sub-problems. Yıldız et al. (2022) reported successful implementation of MILP-based student placement systems at institutional scale, demonstrating that modern solvers can handle educational assignment problems with thousands of decision variables. While the 38-cadet validation provides strong evidence of computational feasibility, empirical testing with progressively larger datasets would be necessary to establish precise performance benchmarks for the complete system implementation. Dong et al. (2024) recommended incremental validation approaches where models are tested at intermediate scales before full deployment, ensuring that computational performance remains acceptable throughout the scaling process.

3.5 Practical Implications for Dormitory Management

The validation results with 38 cadets demonstrate that MILP-based assignment systems provide data-driven decision support, replacing subjective manual allocation with mathematically justified assignments (Andersen et al., 2022). The model achieved 100% constraint satisfaction with solving times of 0.34 seconds (Approach 1) and 0.11 seconds (Approach 2), confirming computational feasibility for real-time applications. In the general framework, administrators can configure weight parameters w_1, w_2, w_3 according to institutional priorities: higher w_1 for distance efficiency, higher w_2 for program cohesion, or higher w_3 for satisfaction (Mou, 2024). The validation study's simplified single-objective formulation offered a clear policy choice between strict constraint enforcement (95% occupancy) and maximum space utilization (100% occupancy), with both approaches achieving 0.00% MIP gap to confirm proven optimality.

The model supports sensitivity analysis for policy exploration, quantifying trade-offs between competing objectives (Cosic et al., 2021). Optimization results establish benchmark standards for evaluating future assignments (Lahza et al., 2024). The implementation using CBC solver version 2.10.3 and PuLP 2.8.0 library demonstrates that the open-source software stack runs on standard computers without specialized hardware or commercial licenses (Cao et al., 2022). Implementation challenges involve data quality assurance and change management for transitioning from manual to algorithm-assisted workflows (Alhasnawi et al., 2025). Beyond operational efficiency, dormitory facility optimization aligns with sustainability goals including green building certification in educational facilities (Rahmasari et al., 2024). Future implementations could integrate environmental considerations such as energy consumption and natural ventilation into the multi-objective framework, supporting universities commitments to sustainable campus development.

3.6 Research Limitations

This study operates within several boundary conditions. The 38-cadet validation (2.5% of full population) provides computational feasibility evidence but not full-scale empirical confirmation; actual performance at 1,550 cadets requires validation before operational deployment. Floor preferences were modeled using literature-based distributions (Lahza et al., 2024) rather than institution-specific survey data, potentially not capturing military education context nuances. Distance calculations assume Euclidean paths with fixed vertical penalties, abstracting actual campus navigation that may deviate 20-40%. The static optimization does not accommodate mid-year reassignments (disciplinary actions, medical needs, program transfers), requiring administrator flexibility for inevitable exceptions. Hierarchical decomposition enables computational tractability but may sacrifice solution quality versus monolithic university-wide optimization quantification of this trade-off remains future work. The model was developed for Indonesian Defense University's standardized infrastructure (150-cadet buildings, 3 floors); generalization to heterogeneous building configurations or civilian contexts requires careful adaptation and pilot validation.

4. CONCLUSION

This research advances dormitory assignment optimization by developing the first MILP-based mathematical framework specifically designed for military education contexts, addressing institutional constraints absent from civilian university optimization literature including gender separation, unit cohesion requirements, and hierarchical organizational structures. The multi-objective model simultaneously optimizes walking distance minimization, study program cohesion, and cadet floor preferences through weighted sum formulation, with empirical validation demonstrating computational tractability: optimal solutions achieved in under 0.5 seconds using open-source CBC solver for 38 cadets, with room occupancy rates reaching 95-100% while maintaining feasibility across all hard constraints. Hypothetical simulation projects scalable performance: 1,550 cadets across 11 buildings achievable within 5-15 minutes using standard hardware, making the framework operationally viable for annual assignment cycles. Theoretically, the study operationalizes dormitory assignment as multi-dimensional optimization balancing spatial efficiency, social cohesion, and user satisfaction dimensions previously addressed only conceptually in educational facility literature. Practically, the framework enables administrators to pilot implementation with 2-3 buildings, conduct weight calibration workshops visualizing policy scenarios, and expand systematically based on validated outcomes. Defense education policymakers should consider standardizing optimization-based dormitory management across military academies nationwide and integrating operations research curricula into military officer training programs. Implementation requires phased deployment: preparation phase (2-3 months) for software installation, pilot phase (6-12 months) for 2-3 buildings, and expansion phase (1-2 years) for full university deployment. Several limitations suggest future research: the 38-cadet validation (2.5% of full population) requires intermediate-scale validation before operational deployment; floor preferences should be replaced with institution-specific survey data; distance calculations could incorporate actual campus path networks for improved accuracy; static optimization could evolve toward dynamic stochastic formulations; hierarchical decomposition potentially sacrifices solution quality requiring quantification; and the model's applicability to civilian universities with heterogeneous building designs remains unexplored, suggesting comparative studies while integrating sustainability dimensions into the multi-objective framework.

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