

Classroom Scheduling Optimization Using Linear Programming: A Critical Review of Models, Utilization Measures and Research Gaps

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Abstract

Every university routinely states that they are understaffed with classrooms, and that many classrooms are left half empty, leaving the Operations Research (OR) problem between these two assertions: that of the understaffed classroom, and that of the half empty classroom. In this paper, the use of linear programming (LP) and its integer extension for the assignment of classes to rooms and time slots is briefly reviewed. Two case applications, one in Landmark University, Nigeria (an aggregate LP) and the other in Uttara University, Bangladesh (two-stage binary integer programme) are presented, and a focused review of 25 studies is conducted between 1992 and 2026. The main room-assignment problem is computationally easy: It can be solved in minutes on real institutions with several hundred to "only" 1100 class meetings by solving the LP relaxation, which is naturally integral, one period at a time, and is an assignment problem in itself. The weakness is in the optimization. There has been a seat hour measure of utilisation since 2009, but each institutional case study maximises at least six different fit measures, which can favour different rooms, report gains based on different baselines and plan against a single enrolment number. Re-running this case with its own data reveals that the case's headline figure of 3,544 seats is higher than the number of seats actually available (2,861). It is illustrated in a five-class example that a tight-fit objective results in 15 students being unseated when there is a heavy load of students, and 2 when there is not. Finally, the paper suggests that the next step in this research is the development of an LP-solvable seat-fit model that is enrolment-robust and a common reporting protocol.

The keywords are operations research, linear programming, integer programming, classroom

assignment, university course timetabling, space utilisation and robustness.

Keywords—operations research; linear programming; integer programming; classroom assignment; university course timetabling; space utilisation; robustness

1. Introduction

Operations Research (OR) takes mathematical and analytical tools to the decision problems that face us when we have limited resources. In the education sector, one of most easily recognised applications is its use in classroom scheduling, where it is used to model a real-life planning process. A typical problem is to determine, for a given class meeting, which room is to be used, and possibly at what time, so that each class has adequate room, no room/class is double booked and the classroom is utilized to the maximum extent.

A linear programming structure can be recognised in the problem. The special case of assigning the classes one period to rooms has an objective function that is linear, constraints of one room per class and one class per room, and is a special case of the assignment problem. When including time periods, lecturers and student groups, it becomes the university course timetabling problem, a general problem which is NP-hard [17] [5]. The problem is also real world, and the time required for manual timetabling was about 3 weeks at Universidad de La Sabana [22], about a month at Universidad Autónoma de Querétaro [23] and about 100 hours at Western Galilee College [21].

The discussion is based on two related objectives. It collects the first 25 studies on the modelling and solving of classroom scheduling using LP and integer programming. It then demonstrates these ideas through two published case studies, Oladejo et al. [15] and Samiuddin and Haq [19] and an illustrative numerical

example to illustrate where things go wrong and go right. The cases that are retained have their data and formulations fully printed out so that results may be checked.

II. Review Scope and Approach

This study adopts the focused narrative review. Not constructed as a systematic review or a meta-analysis. Twenty six research files were collected, of which three were duplicates and 17 were retained as they address classroom/course scheduling as an optimisation problem and the model or results can be investigated. Four of them were excluded because they used only a single classroom in their experiment; four others did not present any mathematical programming model; one did not measure the results (Çaylı and Yılmaz); and one presented results that were projected (Hou). Full details of the excluded papers are listed after the references. These were supplemented by eight additional studies, obtained using backward citation tracking and targeted search, for the areas of utilisation measurement, robustness, and the strategic level. Twenty-four of the 25 were read in full, including Phillips et al. [18] (cited in the version reproduced in the author's doctoral thesis [16]) and Carter and Tovey [4] (which was available as an abstract only and is cited for that and the account of it in Phillips et al. [17]).

The review is organised following the four questions listed above: (1) how is classroom scheduling formulated as an LP or integer programme and where does it stop being a plain LP; (2) what is optimised in the LP, and in particular how is “utilisation” defined; (3) when are exact solvers sufficient, and when do authors resort to

heuristics; (4) what are the limitations and research directions, when the model is applied to real institutions?

TABLE I. Literature streams covered by the review

Literature stream	Representative source	Purpose in this review
Room assignment as an LP	Carter & Tovey [4]; Wasfy & Aloul [24]; Phillips et al. [17]	Explains the linear core and why it is tractable.
Full ILP timetabling	Nakasuwan et al. [13]; Daskalaki et al. [8]; Torres-Ovalle et al. [22]; Urbán Rivero et al. [23]; Arratia-Martinez et al. [2]; Zaulir et al. [26]; Talmor [21]; Suhandi et al. [20]	Shows how real constraints are added and solved exactly.
Utilisation and strategic planning	Beyrouthy et al. [3]; Lindahl et al. [11]; Lemos et al. [10]	Shows how space use has been defined and planned.
Robustness to change	Phillips et al. [18]; Navabi-Shirazi et al. [14]	Shows how plans survive enrolment and capacity changes.
Multi-objective and preference models	Mokhtari et al. [12]; Chen et al. [6]; Al-Sultan et al. [1]	Shows how utilisation is traded against preferences.
Heuristic solution	Cruz-Chávez et al. [7]; Han & Wang [9]	Shows where authors abandon exact methods.
Teaching and survey literature	Winch & Yurkiewicz [25]; Chen et al. [5]	Places the LP approach within the wider field.
Case applications	Oladejo et al. [15]; Samiuddin & Haq [19]	Provide the cases and data used in Section IV.

III. Literature Review

A. Classroom assignment as an optimization model

Perhaps the simplest form of the problem establishes the timetable and decides on which room to allocate to each class. As was done by Wasfy and Aloul [24], it may be presented textbook style, namely, a binary decision variable equals 1 if course i is assigned to classroom j , there is exactly one room allocation per course, each classroom accommodates at most one course, and classrooms that have capacity lower than that of the enrollment are ignored. The objective function aims at minimizing the sum of capacity/enrollment ratios thus rewarding the allocation of large courses to large rooms. The model that has been built for each period at the School of Engineering of the American University of Sharjah was optimized by means of CPLEX in less than a second for all instances.

The rationale behind this approach can be found in Phillips et al. [17]. In case the periods are considered separately, the matrix becomes totally unimodular, so the relaxation of the linear programming (LP) gives integer extreme points, hence the problem may be solved either

by standard LP methods or by the Hungarian method. The loss of integrality appears when periods are linked, e.g., when all the courses must be assigned to the same classroom every period, making the problem to be solved as an integer programming one taking up to 815.7 seconds on University of Auckland's data. It has been previously noted by Carter and Tovey [4] that the conditions that allow the problem to be tractable and the ones that make the problem intractable have been identified, with some institutions regarding it as tractable and others as "next to impossible."

B. Adding time, people and institutional rules

Many of the practical applications include lecturers, student groups, and constraints. Every constraint is linear; however, the overall impact of the constraints destroys the assignment pattern and increases the number of variables. For example, Torres-Ovalle et al. [22] had 2,157,120 variables for Universidad de La Sabana and ran the model on a module-by-module basis by using GAMS. Daskalaki et al. [8] obtained solution times between 2.5 and 95 minutes by using CPLEX 5.1 for up to 19,295 binary variables at the University of Patras. Some of the other studies kept precision intact in the full-scale problem: Urbán Rivero et al. [23] resolved 757 courses and 50 rooms within 403.92 seconds by using Gurobi; Zaulir et al. [26] dealt with 1,098 lectures and 141 rooms within 1,340 seconds; Talmor [21] created a schedule for 236 classes within two minutes by using open-source CBC; and Arratia-Martinez et al. [2] got the optimal solution within 3.16 seconds.

TABLE II. Levels of modelling in classroom scheduling

Modelling level	Basic logic	Main characteristic
Room assignment in one period	Assign each class to one feasible room; each room hosts at most one class.	An LP whose optimum is naturally integral; solved in seconds.
Room assignment with stability	Keep a class in the same room across periods or the whole week.	Fractional LP solutions appear; integer programming is needed.
Full timetabling	Choose period and room together, with lecturer and student-group clash constraints.	Binary integer programme; usually decomposed by stage, programme or period.
Strategic planning	Choose how many rooms of each size and which teaching periods to provide.	Mixed-integer models that trade space against timetable quality.

Decomposition is the device that keeps these models solvable, and it has a cost that only some authors state: a staged solution need not be as good as solving the whole problem at once [19], citing Murray et al..

C. What is being optimised: the meanings of utilisation

Fifteen of the twenty-four non-survey studies consider classroom usage as part of their goals or solutions, although not using it in the same sense. The approaches

of Nakasuwan et al. [13], Mokhtari et al. [12], and Al-Sultan et al. [1] impose penalties for empty seats; Wasfy and Aloul [24] and Samiuddin and Haq [19] minimize capacity relative to enrollment; Urbán Rivero et al. [23] minimize enrollment relative to capacity; Phillips et al. [17] maximize seat usage, leaving some buffer seats available; Lemos et al. [10] maximize the number of students accommodated; and Oladejo et al. [15] maximize seat capacity. These conflicting formulations may imply opposing objectives. For example, for a class of 20 students and two available rooms having 20 and 30 seats respectively, the capacity/enrollment ratio and empty seat penalty will prefer the former room to the latter, while minimizing enrollment/capacity ratio will prefer the opposite room. The ratio-based objective is also more sensitive to smaller class sizes: the difference between 20 seats for 10 students and 40 seats for 10 students amounts to the objective increase of 2.0, while the difference between 110 seats for 100 students and 130 seats for 100 students amounts to the objective increase of 0.2, although the number of vacant seats in both cases is equal to 20.

There is a generally accepted terminology for this type of measure. Beyrouthy et al. [3] define room frequency as the percentage of occupied time slots, room occupancy as the percentage of the room fullness during occupied time slots, and room utilisation as the percentage of occupied seat hours out of total seat hours. According to these authors, the actual institutions have 20-40% utilisation rate, "rooms are occupied half the time, and even when they are in use, they are often only half full," and "if the utilisation level gets above about 60%, it becomes almost impossible to schedule certain course sets." Lindahl et al. [11] found that 21 benchmark instances for ITC-2007 require, on average, 84% more seats than it is possible to provide with a feasible timetable. Navabi-Shirazi et al. [14], for example, when trying to accommodate the Covid-19 distance rules at Georgia Tech, provided 82% of maximal in-person contact hours by reassigning 2,249 sections, while 71% could be provided if each section stayed in its original room. None of the institutional LP case studies uses these terms.

D. Preferences, robustness and solution methods

Of the 24 non-survey papers outside of surveys, 15 include in-classroom usage in their goals or solutions in some way but not in a similar way. The approaches put forward by Nakasuwan et al. [13], Mokhtari et al. [12], and Al-Sultan et al. [1] include a penalty on empty seats; Wasfy and Aloul [24] and Samiuddin and Haq [19] decrease capacity proportionally to enrollment; Urbán Rivero et al. [23] decrease enrollment proportionally to capacity; Phillips et al. [17] maximize seat usage leaving a reserve of extra seats; Lemos et al. [10] maximize the number of students placed; and Oladejo et al. [15] maximize seat capacity. These varied objectives might point to conflicting objectives indeed. For example, in a

class of 20 people where there are two possible rooms – with 20 and 30 seats, respectively – the first approach would suggest using the first room and the second approach would advocate for the second one. Also, the latter would be especially sensitive to smaller classes, where moving from 20 seats for 10 people to 40 seats for 10 people increases the objective value by 2.0, while moving from 110 seats for 100 students to 130 seats for 100 students increases it only by 0.2. However, both examples leave 20 empty seats.

There is conventional terminology for the type of criteria used in this paper. Beyrouthy et al. [3] define room frequency as a percent of time slots that are occupied, room occupancy as a percent of fullness of the room during occupied time slots, and room utilization as a

percent of occupied seat hours divided by total seat hours. They note that in reality universities have utilization of 20–40%, where rooms are occupied half of the time and are rarely filled up even during their occupancy, and in addition when utilization is higher than 60%, some course pairs cannot be scheduled anymore. Lindahl et al. [11] reported that out of 21 benchmarks used in ITC-2007 the timetable requires 84% more seats than could be practically provided. Navabi-Shirazi et al. [14] managed to provide 82% of maximal in-person contact hours by shifting 2,249 sections, while 71% could be provided if sections stayed in their initial rooms. No university LP case study uses these terms.

E. Reported outcomes across studies

Table III summarises the studies with institutional or benchmark data. Figures are as reported by the authors.

TABLE III. Studies reporting institutional or benchmark results

Ref.	Study	Setting	Model and objective	Software	Reported outcome
[13]	Nakasuwan et al. (1999)	SIIT, Thailand	BILP; min cost + empty-seat loss	LINGO	All constraints met; no comparison
[8]	Daskalaki et al. (2004)	Univ. of Patras, Greece	Six-index BILP	CPLEX 5.1	2.5, 18.5 and 95 min
[24]	Wasfy & Aloul (2007)	AUS, UAE	0-1 ILP per slot; min capacity ÷ enrolment	CPLEX	Optimal in <1 s
[3]	Beyrouthy et al. (2009)	Sydney building, Australia	Matching LP/IP + simulated annealing	Not named	Safe utilisation below ~60%
[25]	Winch & Yurkiewicz (2014)	Pace Univ., USA	Assignment-type LP (student view)	Excel Solver	75% of 127 students built a model
[22]	Torres-Ovalle et al. (2014)	La Sabana, Colombia	BILP by programme	GAMS	Cost 7,421 → 4,782
[17]	Phillips et al. (2015)	Auckland, NZ; ITC-2007	Set-packing IP, lexicographic	Gurobi	Event steps 0.5–5.5 s
[7]	Cruz-Chávez et al. (2016)	UAEM, Mexico	Constraint model; feasibility	Constructive heuristic	Feasible in 12 of 30 runs
[18]	Phillips et al. (2017)	Auckland, NZ	IP repair of timetable	IP in heuristic	Over-enrolment fixed in <1 s per IP
[11]	Lindahl et al. (2018)	ITC-2007 (Udine)	Bi-objective MIPs	Gurobi	84% more seats than needed
[15]	Oladejo et al. (2019)	Landmark Univ., Nigeria	Continuous LP; max seats	AMPL, MINOS	3,544 seats (2,066 on recount)
[19]	Samiuddin & Haq (2019)	Uttara Univ., Bangladesh	Two-stage BILP	Python	6.72 s; 92.21% happy slots
[10]	Lemos et al. (2019)	IST Lisbon, Portugal	Two-stage ILP vs greedy	CPLEX	Greedy within 1.1–1.4%
[23]	Urbán Rivero et al. (2020)	UAQ, Mexico	ILP; min enrolment ÷ capacity	Gurobi	Optimal in 403.92 s
[2]	Arratia-Martinez et al. (2021)	Mexican department	ILP, no rooms	CPLEX	Optimal in 3.16 s
[12]	Mokhtari et al. (2021)	IAU Najafabad, Iran	Multi-objective MIP, ϵ -constraint	GAMS, CPLEX	Penalty 17 → 15
[14]	Navabi-Shirazi et al. (2022)	Georgia Tech, USA	Hierarchical multi-criteria IP	Gurobi	82% vs 71% contact hours
[26]	Zaulir et al. (2022)	UMT, Malaysia	MILP; max preference	AIMMS, CPLEX	Optimal in 1,340 s
[6]	Chen et al. (2022)	Unnamed faculty	Integer model + GA	GAMS; GA	Small test instance
[21]	Talmor (2024)	Western Galilee, Israel	ILP, no rooms	Python, CBC	1.45–1.84 min per run
[9]	Han & Wang (2025)	Beijing Forestry Univ., China	MILP via GA–DP hybrid	Custom heuristic	Rooms used up to ~29.27%
[20]	Suhandi et al. (2025)	Maranatha Univ., Indonesia	ILP; min deviation from availability	CPLEX	10.42 s
[1]	Al-Sultan et al. (2026)	Kuwait Univ., Medicine	Two-stage IP; min empty seats × preference	GAMS	20 s; manual 57% worse

F. Literature synthesis and research gap

Together, the papers reveal five recurring themes. First, the room-assignment problem at hand represents an integer LP program, which can be solved by exact algorithms in seconds or minutes in realistic cases. Second, decomposition has been a standard technique in making more elaborate timetabling models tractable. Third, utilization is the objective that comes up the most often; nevertheless, there are at least six definitions of utilization used in case studies of institutional timetables and each definition encourages a different assignment schedule. Fourth, the robustness of timetables to variations in enrollment and capacity has been investigated in a different research track, whereas the only case study to consider the variation in enrollment level in their evaluation is that of Al-Sultan et al. [1]. Fifth, all cases involve comparing a particular institution with its own manually generated timetable using different baseline figures.

It appears evident that a gap arises in formulation and measurement but not in solution methodology. All of the necessary elements for proper planning of classroom utilization—an hour of seat capacity as a utilization measure and the objectives to protect against the changes in enrollment—are known, but have yet to be incorporated in the LP-solvable classroom assignment models used in practice. These models make ad hoc fit ratios and produce non-comparable figures for a single

enrollment prediction. The identified gap involves fifteen out of twenty-four non-survey studies.

IV. Case Studies

Two case examples have been chosen as representatives of extremes in the literature; one example is the single paper in the literature using purely linear program (LP) approach and another is a complete binary integer program that considers time, people, and rooms. Both case studies provide their data sets and model formulations, allowing for their replication.

A. Case A: Landmark University, Nigeria [15]

Oladejo et al. [15] examine classroom allocation at Landmark University, which had 2,522 students across three colleges and 32 classrooms of 19 capacity types, from 36 to 394 seats. The authors observed congestion in some lecture rooms while others went unused, and asked how much student capacity the existing rooms could support. Room and enrolment data came from the university's timetable committee. Let x_j denote the number of rooms of type j used and c_j the objective coefficient for that type. The model maximises total seats offered:

$$\text{Maximize } P = \sum_j c_j x_j \quad (1)$$

subject to five student-level constraints, a ceiling of 32 rooms, x_j being less than or equal to the number of rooms of type j and $x_j \geq 0$. The problem has been coded in AMPL and solved with MINOS 5.51 solver reporting $P = 3,544$ seats after 10 iterations. The authors find out that an extra 1,022 students can be served by the current inventory of rooms, generating revenues of ₦585,606,000.

TABLE IV. How the LP objective reaches 3,544 seats (recomputed from Oladejo et al. [15])

Room type	Rooms	Seats per room	LP coefficient	LP value of x	Seats counted by LP	Seats actually available
A11, A14	2	72	144	2	288	144
B04, B14, B24	3	91	273	3	819	273
A04, A21, A24	3	98	294	3	882	294
B01, A215	2	100	200	2	400	200
Six single-room types	6	92 to 394	= capacity	1 each	1,155	1,155
Total	16				3,544	2,066

The paper's own room table shows that all 32 rooms have a capacity of 2,861, and an optimum is 3,544, which is 683 more than the physical stock. Each type is counted two or three times in types with more than one room, since coefficient is always the total capacity of the type ($144 = 2 \times 72$) and the variable is capped by the number of rooms. The authors' own estimate for the rooms used is 2,066 seats, which is the number used when the same solution is provided once per room. None of the student level constraints in the AMPL code is binding because all have a value of 2,861, and none contains any time dimension. With its own information the 32 rooms offer

2,861 seats for any given time, with 339 more seats than the total enrolment.

B. Case B: Uttara University, Bangladesh [19]

In the Department of Electrical and Electronic Engineering, Uttara University, Samiuddin and Haq [19] schedule more than 1000 students in 31 groups, 51 instructors and 184 courses in 19 general rooms and 10 laboratories, in nine slots during three days of summer 2018. Consider the variables x_{ijklmn} to be 1 if student group m is taught by instructor l in room i on day j in slot k . The room capacity divided by the size of the group, plus the penalty for each instructor preference, H_{jkl} (where $H =$ "happy", $h =$ "okay", and $H = H > 1$ otherwise):

$$\text{Minimize } Z = \sum c_{im} H_{jkl} x_{ijklmn} \quad (2)$$

No instructor or group conflicts; one course per room per period; adequate room for each group; Laboratory courses only in laboratories. Labs are first and theory classes are second; only actual instructor/course/class combinations are variables. The model was developed in Python and the authors claim the simplex method is used to optimize the model.

TABLE V. Model sizes and solve times reported by Samiuddin and Haq [19]

Approach	Variables	Solve time
Proposed two-stage model, true variables only	16,241	6.72 s
Single stage, true variables only	22,302	43.09 s
Single stage, all variables	4,814,145	Ran out of memory

The final schedule achieved 92.21% of the 'happy' slots, 68.42% of the 'okay' slots and an 'average room efficiency' of 93.67%. The model was reduced by over 99% by taking out variables that could not possibly occur. The single-stage model was solved, but no objective value was reported, which means the cost of decomposition was not known, "room efficiency" is not

defined and the paper does not mention how integrality was achieved other than by the simplex method.

V. Comparative Solution Results

An illustrative example was solved for one teaching period to compare the utilisation objectives on the same terms. Data are hypothetical and not actual data of University. Seven rooms (R1–R7, with 30, 40, 60, 60, 90, 120 and 150 seats) must host five classes with planning enrolments of 25, 38, 55, 58 and 110 (C1–C5). Because rooms are booked before enrolment closes, each class also has a low and a high scenario (C1: 22–32; C2: 36–40; C3: 52–58; C4: 55–61; C5: 99–132). With $x_{er} = 1$ if class e is placed in room r and w_{er} a fixed score, the model is:

$$\text{Optimize } Z = \sum_e \sum_r w_{er} x_{er} \quad (3)$$

subject to

$$\sum_r x_{er} = 1 \text{ for each class } e \quad (4)$$

$$\sum_e x_{er} \leq 1 \text{ for each room } r \quad (5)$$

$$0 \leq x_{er} \leq 1 \quad (6)$$

Four scores from the literature were evaluated: (A) minimising capacity/ enrolment; (B) minimising number of empty seats; (C) minimising enrolment/ capacity (as proposed by Urbán Rivero et al. [23]); and (D) maximising a strong seat-fit score (the percentage of seats in the scenarios minus the λ times the probability of overflow; $\lambda = 1$). The model was solved as a plain LP using HiGHS solver in Python's SciPy library, and as expected by the assignment structure, all the variables took values of exactly 0 or 1.

TABLE VI. Results of the illustrative five-class example under four objectives

Objective	Optimal plan (C1–C5)	Seats in use	Occupancy (base)	Utilisation (base)	High scenario: overflow
(A) Min capacity ÷ enrolment	R1, R2, R4, R3, R6	310	92.3%	52.0%	3 classes, 15 students
(B) Min empty seats	R1, R2, R4, R3, R6	310	92.3%	52.0%	3 classes, 15 students
(C) Min enrolment ÷ capacity	R3, R4, R5, R6, R7	480	59.6%	52.0%	None
(D) Robust seat-fit, $\lambda = 1$	R1, R2, R3, R5, R7	370	77.3%	52.0%	1 class, 2 students

As can be seen, it is actually the objective that determines how full or secure the room plan is, and not the solver. Objectives (A) and (B) provide the same tight plan with an occupancy rate of 92.3%, but if the enrolment is high, then the three classes are running out of rooms, and 15 students are without a seat. Objective (C) has all classes in a larger room and the usage rate for the rooms is 59.6%. The fit of the robust objective (D) is tight when enrolment remains stable, and provides space for the two volatile classes to grow, with the latter two classes having a maximum of 15 points of capacity lost. As the seat-hour utilisation of all plans is 52.0%, they can't be identified separately by seat hour utilisation, and must be reported with occupancy and overflow.

The varying λ represents the trade off in a priced decision. The tight plan (92.3% occupancy, 15 students unseated in high scenario) is returned by the robust model at $\lambda = 0$ or 0.25; at $\lambda = 0.5$, the largest class is returned (84.1%, 3

unseated); and at $\lambda = 1$, the two classes that are volatile are returned (77.3%, 2 unseated); and at $\lambda = 2$, all three volatile classes are returned (71.5%, none unseated). The figures used are for this illustrative data set and are not expected to be generalised as expected savings for any institution.

A. Interpretation in light of the literature

The example is representative of the responsibilities given to the assignment LP in the literature: it is fast, transparent and naturally integral [17]. It also provides an actualization of the measurement problem of Section III-C. The capacity-ratio objective of Wasfy and Aloul [24] and Samiuddin and Haq [19] and the empty-seat objectives of Nakasuwan et al. [13] and Al-Sultan et al. [1] yield the tightest plans that are most vulnerable to growth in enrolment of the type experienced at Auckland as reported by Phillips et al. [18]. By considering overflow as an explicit cost, as would be done by Phillips

et al. [17] using the robustness of the spare-seat approach, the plan changes but the solution method does not. On the other hand, the outcome should be interpreted in terms of the mechanism rather than as proof that the objective is always to be achieved that way.

VI. Critical Analysis

A. Strengths

Transparency: The LP and ILP models utilize a linear constraint for each scheduling rule, thus allowing administrators to observe the reasons for which a room was denied, and which periods are overbooked [17], [21].

Experts' optimality and infeasibility: Exact solvers either certify the best plan or prove it is impossible given the current rules [24]; while a manual timetable may have

been able to be constructed at the time, an exact model would have immediately spotted that this was the case.

Real instances, speed: Solve times are 2-95 minutes, manual is 2 weeks to 1 month.

Accessible tools: The models are solved using a variety of widely-used tools, including CPLEX, Gurobi, GAMS, or the free tool CBC solver, and Excel's Solver. [25]

Reusable for planning: After the model is constructed, it can be rerun for various planning scenarios like fewer rooms [22, 20] or more students [1].

B. Limitations

The first restriction is the deterministic approach to enrolment. Rooms are allocated before enrolment closes, but most institutional models, and a tight-fit objective is the most growth sensitive policy. Due to capacity constraints, it was impossible to have all pupils seated in any room plan at Lisbon, overbooking by 10-35% [10]. The second is that the goal is an ill-defined, and not always consistent, measure of utilisation: in case A this is particularly evident.

Another restriction is that of reporting results. Table VII shows that several improvements are calculated based on the improved and not the original figure, which exaggerates the improvement. All of these differences do not reverse the direction of a study's improvement, but they all help to account for why results can't be pooled.

TABLE VII. Reported improvements recomputed against the original baseline

Study	Quantity	Reported change	Against original	Note
Wasfy & Aloul [24]	Objective weight, 10 slots	"On average 25%"	22.3%	Mean of slot-level changes
Torres-Ovalle et al. [22]	Classrooms, 60 → 46	30.4%	23.3%	$30.4\% = 14 \div 46$
Torres-Ovalle et al. [22]	Teaching hours, 2,066 → 1,727	19.5%	16.4%	$19.5\% \approx 339 \div 1,727$
Torres-Ovalle et al. [22]	Cost, 7,421 → 6,407	15.8%	13.7%	$15.8\% = 1,014 \div 6,407$
Mokhtari et al. [12]	Priority penalty, 17 → 15	About 13%	11.8%	$13\% \approx 2 \div 15$

Structural constraints are other limitations. In almost all cases, it is one institution in one semester; preference weights are arbitrarily selected without rules or simulated [26]; and most work remains operational, although Lindahl et al. [11] suggest that the strategic decisions of allocating room capacity for "staged solutions" are "rarely changed or even discussed". Thirdly, this review was compiled using supplied papers and citation tracking

instead of a systematic search in databases and one paper [4] was not available as a full paper.

VII. Implications and Future Research

The literature and the two examples indicate that there is a good potential for the use of LP-based classroom models as decision tools: a department or faculty may be scheduled exactly in seconds and minutes; even a simple model is sufficient to indicate which rules make the timetable infeasible. The caution is for the target. The decision maker needs to ask: "what was the baseline and against whom was utilisation improved?" before believing statements like "utilisation improved by X%".

This gap identified in III-F is addressed by the following research objective: the development of an LP-solvable classroom assignment model with a clear objective function of seat utilisation and with the possibility of considering the enrolment as an uncertain variable, as well as a collective set of utilisation indicators with which to compare the results obtained in each institution. The following are four research questions. In what ways do the assignments differ with respect to the same timetable in the assignments generated by the different utilization objectives found in the literature? (2) Is there an objective for seat fit that preserves the totally unimodular structure when there is uncertainty about enrolment that can also be solved as an ordinary LP? (3) Does it give any benefit in terms of lessening overflow when the enrolment is realised? (3) How much benefit in terms of occupancy does it give? (4) What minimum set of indicators should studies report?

The model proposed here is the one-period assignment LP from Section V with only the scores changed. Let K be a set of enrolments, and e be a class, and denote its enrolment by n_e^k and the capacity of a room by s_r :

$$w_{er} = (1/|K|) \sum_k \min(n_e^k, s_r) \div s_r - \lambda (1/|K|) \sum_k [n_e^k > s_r] \quad (7)$$

The first term is a cost for the closeness of the fit, and the second term the cost of the risk of overflow; the latter is done as in the work of Lemos et al. [10] which uses the number of seated students as the smaller of the two numbers, enrolment and capacity. Note that the model remains an assignment LP regardless of the scenario set and lambda. The results should then be presented as the frequency, occupancy and seat-hour utilisation of Beyrouthy et al. [3], the overflow rate given the realised enrolment, any percentage change compared to a known point, and the solver, instance size and time.

There are a number of additional directions. The strong model should be trialled at an institution on its own time frame, using a minimum of two semesters of enrolments. If models are solved in stages, the same model should be solved on a smaller model to demonstrate what loss of decomposition entails. However, before being labelled as necessary, heuristics should be evaluated against exact solvers using the same real data, as Lemos et al. [10] did. Linking to operational and strategic decisions is possible as in Lindahl et al. [11]. Repair models for changes during the semester [18], [14] can be brought into single-faculty practice. It is important that real preference data is gathered and not simulated, so as to give a measure of the trade-off between people and space as Mokhtari et al. [12] start to do.

VIII. Conclusion

Classroom scheduling is a method that structures a university's room booking problem into a measurable optimization problem. The research papers reviewed

point out that its basic problem, namely, placing one period into rooms, is an assignment problem whose LP relaxation is naturally integral, and that exact solvers solve real faculties in seconds to minutes. If we include the rules of the lecturers, student groups and institutional rules, the models are turned into integer programmes and decomposition remains tractable.

It is in the two cases that the difficulty lies. An LP returned these 3,544 seats at Landmark University where the capacities of the rooms is 2,861, feeding the revenue projection of ₦585.6 million. A high level of efficiency was reported for the room at Uttara University, but using a programme it never built. When student enrolment is high, the illustrative example demonstrated that a tight-fit objective results in 15 students being unseated, whereas an enrolment-robust objective results in 2 students being unseated, and the solution method remains the same..

When applying the LP model in the future, the major difficulty is to keep the transparency and speed of the model, but also to measure the utilisation on a common scale and to be able to deal with uncertain enrolment. This offers a natural progression for research from basic models of seat fit to strong models that are comparable and informed by research.

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