A Hybrid Quantum Annealing Algorithm for Solving a Constraint-Based University Timetabling Problem

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Abstract

University timetabling is a classical NP-Hard combinatorial constraint problem that involves scheduling of courses, lecturers, students, classrooms, and timeslots while satisfying a set of constraints, with the main goal of minimizing conflicts. To solve this problem, we propose a novel Quantum Annealing and Topological Data Analysis (QA–TDA) algorithm that starts with an initial feasible solution, followed by iterative refinement using Quantum annealing configurations. TDA analyses the optimization landscape through persistent homology by detecting promising regions of interest in the solution space, which are clustered and subjected to quantum re-annealing using customized Hamiltonians-adaptive annealing schedules. QA-TDA model achieves a balance between global exploration and local exploitation, which improves convergence efficiency and solution robustness. Experimental results demonstrate that our hybrid model consistently outperforms baseline models across all evaluation metrics. In particularly on the most complex dataset, QA– TDA achieved a Conflict-Free Rate (CFR) of 94.3%. Additionally, an ablation study was conducted to validate the contribution of each component of the proposed model. Furthermore, clustering and K-Nearest Neighbour (K-NN) analyses confirm the robustness and consistency of the proposed approach across datasets of varying sizes and complexity. These findings highlight the great performance, scalability, and reliability of the integrated QA–TDA model for real-world academic scheduling applications.

Key Words: Academic Timetabling, Quantum Annealing Technique, Topological Data Analysis Method

Introduction

Solving a university teaching timetable is a challenging combinatorial optimisation problem that requires assigning courses to time slots, rooms, and instructors while satisfying a wide range of hard and soft constraints, including classroom capacity, institutional policies, pedagogical requirements, and stakeholder preferences. An effective timetable must maximise resource utilisation while minimising conflicts, idle times, and inefficiencies such as underutilised facilities or uneven teaching loads. Because of the many variables needed, the solution space grows exponentially, rendering the problem NP-hard and computationally intractable for exact optimisation in real-world settings (Davison et al., 2025; Park et al., 2025; Khokale et al., 2025).

University timetabling has been studied under several formulations, notably the Examination Timetabling Problem (ETP), the Course Timetabling Problem (CTP), and the Curriculum-Based Course Timetabling Problem (CB-CTT). While ETP focuses on scheduling examinations without student conflicts, CTP addresses the allocation of teaching activities across time periods, and CB-CTT introduces additional complexity by incorporating curriculum-level constraints. Despite structural similarities, these formulations differ significantly in practical outcomes, with CB-CTT presenting the highest level of complexity due to overlapping curricular requirements.

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Academic timetabling shares similarities with other resource allocation problems such as nurse rostering, workforce scheduling, and job-shop optimisation. However, the multi-layered institutional constraints and pedagogical requirements inherent in higher education significantly increase its complexity. Consequently, general-purpose optimisation solvers often perform poorly unless tailored specifically to the domain.

Traditional approaches include exact techniques for optimization such as Integer Linear Programming (ILP) and Constraint Programming (CP), which are effective for small-scale instances but become computationally infeasible as problem size increases. To overcome these limitations, metaheuristic techniques such as Genetic Algorithms (GA), Simulated Annealing (SA), Tabu Search, and Ant Colony Optimisation (ACO) have been widely adopted. These methods improve global search capability and avoid local optima, with hybrid approaches such as memetic algorithms and Adaptive Large Neighbourhood Search demonstrating strong performance on benchmark datasets. However, metaheuristics often lack generalisability, require extensive problem-specific tuning, and offer limited interpretability.

Recent advances have introduced machine learning approaches, including predictive models and reinforcement learning, to generate adaptive timetabling solutions. While these methods show promise, they are typically treated as “black-box” models, providing limited transparency into the structure of the solution space. This lack of interpretability poses challenges in educational contexts, where explain ability and accountability are essential. Furthermore, such approaches often require large training datasets and do not explicitly capture the geometry of feasible and infeasible solution regions.

The problem in this study is formulated as a many variables binary discrete model comprising a big set of accompanying decision variables. The decision variables establish how the courses will be assigned to times (defined by X_{jlm}), how the classrooms for conducting the courses, e.g., Y_{jo}, shall be allocated, and how units will be allocated and subsequently scheduled for courses (defined by Z_{ij}) as well as how lecturers are scheduled (defined by A_{jn}). The objective of this research is to build an optimal timetable that satisfies institutional policies while achieving the key performance metrics as follows: (i) conflict-free ratio; (ii) resource utilization; and (iii) minimization of idle time.

To overcome these limitations, this study proposes a novel hybrid timetabling model of Quantum Annealing (QA) with Topological Data Analysis (TDA). The problem is defined as a Quadratic Unconstrained Binary Optimisation (QUBO) model, where institutional constraints are encoded as binary variables. Quantum Annealing is then employed to identify low-energy configurations, leveraging quantum tunnelling to efficiently explore complex solution landscapes. This approach enables the generation of high-quality initial schedules that are structurally coherent and largely conflict-free.

TDA is incorporated to analyse the geometric structure of the solution space using persistent homology. This allows the identification of near-optimal solution clusters, recurring constraint violation cycles, and infeasible void regions. These topological features provide valuable insights into the distribution of feasible solutions and can guide the optimisation process toward more promising regions.

A key contribution of this work is the integration of QA and TDA within a closed-loop adaptive model. Insights derived from TDA are used to iteratively refine the QUBO formulation, directing the quantum optimiser toward regions with higher solution quality. This synergy enhances both optimisation efficiency and interpretability, enabling dynamic conflict resolution, improved resource utilisation, and more balanced workload distribution.

This study is a hybrid of Quantum Annealing and Topological Data Analysis for making an intelligent university course timetable. The following are the main contributions:

A comprehensive formulation based on QUBO capturing structural together with operational constraints.

Persistent homology application to analyse and interpret the topology of the solution space.
A novel closed-loop QA–TDA optimisation model for adaptive and interpretable timetabling.
Empirical evaluation through simulation and benchmarking against classical methods using metrics such as Conflict-Free Ratio (CFR), use of resources, and idle time.

This work contributes to advancement of educational scheduling by integrating quantum computing with topological analysis, offering a scalable, interpretable, and high-performance solution for complex timetabling problems.

Problem Definition

The problem statement presented in this section is a continuation of the problem as defined in the Introduction, providing a detailed formulation of the constraint-based university timetabling problem and the proposed Hybrid Quantum Annealing Algorithm. Table 1 is presented below to summarize the key parameters and variables used in the model.

Table 1. Model Parameters and Descriptions

Parameters	**Description**
s	Represents number of student groups or classes
p	Represents number of lecturers or instructors
r	Represents number of available classrooms
c	Represents number of courses offered
d	Represents number of teaching days in a week (5 days)
t	Represents number of teaching periods per day (four periods: 7–10 a.m., 10 a.m.–1 p.m., 2–5 p.m., 5–8 p.m.)
$Xjlm$	Represents binary variable equal to 1 if course j is scheduled on day l during period m, and 0 otherwise
Yjo	Represents a binary variable equal to 1 if course j is allocated to room o, and 0 otherwise
Z_{ij}	Represents a binary variable equal to 1 if course j is assigned to student group i, and 0 otherwise
Ajn	Represents a binary variable indicating whether course j is assigned to lecturer n (1 if assigned, 0 otherwise)
$St(i)$	Represents the total number of students enrolled in class i
$C(o)$	Represents the maximum capacity of room o

The main objective of this study is to generate an optimal class timetable that is free of scheduling conflicts, maximizes the utilization of resources (such as courses, instructors, and classrooms), and minimizes idle time between sessions. To accomplish this, the model defines binary decision variables that specify the timing and location of each course (e.g., Monday at 9 am in Room 108). The formulation employs several sets, including s (all scheduled classes), p (all instructors), r (all classrooms), c (all courses offered by the institution), d (teaching days), and t (available time slots).

Decision Variable Constraints

At any given day and time period, a lecture room may host at most one course:

$$\sum_{j=0}^{c} X_{jlm} Y_{jo} \leq 1 \; \forall, l \in \{1, \dots, t\}, o \in \{1, \dots, r\}$$

The total teaching load for each lecturer is a maximum of ten units per semester:

$$\sum_{j=1} A_{jn} \leq 10, \forall, n \in \{1, \dots, p\}$$

Each course must be allocated to a classroom with a seating capacity enough for all enrolled students:

$$\sum_{t=0}^{s} St(i)Z_{ij}\,Y_{jo} \leq C(o)\ \forall, j\ \in \{1, \ldots, c\}, o \in \{1, \ldots, r\}$$

Visiting Constraints

At most one course to be allocated a theory-oriented classroom at any given time:

$$\sum_{j=0}^{c} Y_{jo} \leq 1\ \forall, o\ \in R_{Theory}$$

Practical laboratories are limited to a single course assignment at any given time:

$$\sum_{j=0}^{c} Y_{jo} \leq 1\ \forall, o\ \in R_{Practical}$$

Conference and seminar rooms may host only one course at the same time:

$$\sum_{j=0}^{c} Y_{jo} \leq 1\ \forall, o\ \in R_{Comference}$$

Binary Decision Variables

Every decision variable in the model is binary, getting values from the set {0,1} (Joe, 2025, Park et al., 2025):

$X_{jlm}, Y_{jo}, Z_{ij}, A_{jn} \in \{0,1\}\ \forall\ j,l,m,o,i,n$

Objective Function: Predictive–Prescriptive Optimisation with Performance Metrics

The main goal is to design an adaptive, optimal course timetabling solution that reduces inefficiencies while improving the overall quality of the schedule. These major metrics gauge how effective a timetable model(s) is:

- Conflict-Free Ratio (CFR): The maximum % (Size) of all scheduled assignments that do not have scheduling conflicts, including the other assignments scheduled for at same time.

$$CFR = \frac{\text{Number of Conflict} - \text{Free Assignments}}{\text{Total Number of Assignments}}$$

- Resource Utilization (RU): Refers to the ideal usage of all classrooms and available time slots.

$$RU = \frac{\sum Y_{jlm} + \sum Y_{jo}}{r.d.t}$$

- Computational Time (CT): The total time since the beginning of running the entire algorithm (empirical measurement).
- Idle Timeslots: Refers to time slots not assigned to classes; should be at a minimum for both the instructor and students.

$$\min[\left(dt - \sum_{j=1}^{c} A_{jn} \sum_{i=1}^{d}\sum_{m=1}^{t} X_{jlm}\right) + \left(dt - \sum_{j=1}^{c} Z_{ij} \sum_{i=1}^{d}\sum_{m=1}^{t} X_{jlm}\right)]$$

To account for real-world constraints, together with what the stakeholders prefer, we developed an optimisation model that integrates both predictive and prescriptive elements.

Predictive Optimisation — aims at reducing deviation from the expected scheduling pattern, (Aygül, 2025, Abdulrehman et al, 2025).

$$\min \sum_{j=1}^{c}\sum_{i=1}^{d}\sum_{m=1}^{t} |P_{jlm} - X_{jlm}|$$

Prescriptive Optimisation — improves a timetable through the use of predictive insights while trying to balance the amount of work assigned.

$$\min[\sum_{j=1}^{c}\sum_{i=1}^{d}\sum_{m=1}^{t} |P_{jlm} - X_{jlm}| + \min\left(dt - \sum_{j=1}^{c} A_{jn} \sum_{i=1}^{d}\sum_{m=1}^{t} X_{jlm}\right) + \left(dt - \sum_{j=1}^{c} Z_{ij} \sum_{i=1}^{d}\sum_{m=1}^{t} X_{jlm}\right)]$$

This formula enables, delivery of flexible conflict-free scheduling plan uses classroom space, classroom time, and employee human resources efficiently while accommodating institutional policies and stakeholder preferences.

Proposed Method

In developing a model for university course scheduling, we adopted a hybrid optimisation approach that combines QA with TDA. The approach incorporates a Quadratic Unconstrained Binary Optimization (QUBO) model to represent an energy function that caters for all of the institutional constraints in a problem-specific way. For every course c_i, time slot t_j, and classroom r_k, the QUBO formulation defines a binary variable q_{ijk}, where $q_{ijk} = 1$ signifies that course c_i is scheduled in room r_k at time t_j, (Tole & Fondo, 2026, Naeem et al., 2025).

The overall total energy of the system is the sum of penalty terms that includes violations of the hard constraints related to scheduling, such as instructor overloads, room conflict, or schedule overlaps among students.

$$E(X) = \sum_{i.j.k} q_{ijk} \ .P_{conflict}(c_i, t_j, r_k) + P_{room}(c_i, t_j, r_k) + P_{teacher}(c_i, t_j)$$

The quantum Hamiltonian $H(X)$ is a representation of the energy function and is worked out by using its lowest energy state (the lowest energy configuration) to determine the timetable that is optimal. After formulating the QUBO and providing a feasible timetable as per Algorithm 1, the first step/question in this method is to perform the two activities together. The final state will be a schedule.

Algorithm 1: QUBO Initialization and Quantum Annealing Formulation

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```
Input: Capture Course set $C$, time slots $T$, classroom set $R$, instructor set $S$, constraint set $F$, maximum number of iterations $N_{max}$, initial annealing temperature $T_0$;
Output: Initial timetable $X^{(0)}$, associated energy function $E(X)$, and problem Hamiltonian $H(X)$;
Generate an initial feasible timetable $X^{(0)}$ randomly;
Associate each course $c_i \in C$ with a unique time–room combination $(t_j, r_k)$ using binary variables $q_{ijk}$;
Formulate the energy function $E(X)$ by embedding constraint violations as penalty terms for conflicts, room usage, and lecturer availability;
Transform the energy formulation $E(X)$ into the corresponding Hamiltonian $H(X)$ that is suitable for quantum annealing;
Give the annealing temperature schedule: $T(t) = T_o \left(1 + \frac{t}{N_{max}}\right)$
```

Following creation of the initial configuration of the quantum annealer, quantum annealing is done to lead the system to states with lower energy in a number of steps. A Hamiltonian guiding the quantum annealing process changes over time; initially, the Hamiltonian crafts a simple to prepare system, while ultimately, the Hamiltonian maps the full set of constraints on the final quantum state.

$$H(X,t) = A(t)H_{init} + B(t)H_{final}\,, A(t) = \frac{N_{max} - t}{N_{max}}\,, B(t) = \frac{1}{N_{max}}$$

In each iteration, the algorithm computes the energy of the current state and probabilistically transitions to new configurations according to a Boltzmann distribution. The complete procedure is presented in Algorithm 2.

When Quantum Optimization is finished, Topological Data Analysis provides a means of showing the Optimising Landscape structure of any created by the algorithm (Tole & Fondo, 2026, Fondo et al., 2025, Fondo & Tole, 2026). A distance matrix deriving from candidate schedule distances is produced and used to build a Vietoris-Rips Simplicial Complex. Consistent topological features from this construction are collated into a persistent homology model, revealing clusters, loops, and regions suitable for more localised refinement. The implementation of this approach is presented in Algorithm 3.

As shown in Algorithm 4, a second refinement level applies quantum computation to each suitable region using target quantum annealing routines based on custom Hamiltonians and specially designed annealing schedules.

Algorithm 2: Quantum Annealing-Based Course Timetabling Optimisation

```
Input: Represent initial timetable $X^{(0)}$, problem Hamiltonian $H(X)$, annealing schedule $T(t)$, maximum iterations $N_{\max}$;
Output: Optimized timetable $X^*$, corresponding minimum energy $E^*$;
Set $X \leftarrow X^{(0)}$ & $E^* \leftarrow E(X^{(0)})$;
for $t = 1$ to $N_{\max}$ do
    Adjust the time-dependent Hamiltonian $H(X, t)$ using annealing coefficients $A(t)$ and $B(t)$;
    Update the system temperature according to $T(t) = T_o \left(1 + \frac{t}{N_{max}}\right)$;
    Calculate the energy of the current state: $E(X_t) = \sum h_{ijk} q_{ijk}$ ;
    if $E(X_t) < E^*$ then
        Assign $X^* \leftarrow X_t$ and update $E^* \leftarrow E(X_t)$;
    end
end
return $X^*$, $E^*$;
```

Algorithm 3: Topological Analysis of the Timetable Solution Space

```
Input: Selected timetable solutions $\{X_t\}$, persistence threshold $\tau$;
Output: Filtered topological signatures and candidate regions for refinement;
Evaluate pairwise solution distances: $d(X_i, X_j) = \sum_k | q_{ijk}^{(X_i)} - q_{ijk}^{(X_j)} |$
Form the Vietoris–Rips simplicial complex $C(X)$ from the distance measure;
Perform persistent homology by computing homology categories $H_n(C(X))$ for $n = 0,1$;
Pick topological features that persist past the threshold $\tau$;
Select the regions of interest in the solution space for targeted quantum re-annealing;
```

This approach maximizes optimization chances within those regions that show the greatest potential for overall improvements, (Karema et al., 2024, Zhou et al., 2025). The model perpetuates a balance between global exploration and local refinement via repetitive hybrid processing. By integrating QA with TDA in the optimisation procedure, the approach enhances both efficiency and solution quality as it offers structural insights into the solution space. This enables universities to develop timetables that are conflict-free, resource-efficient, adaptable to policy modifications, and scalable to suffice the demands of large academic organisations.

Algorithm 4: Hybrid Quantum Annealing-TDA Refinement Procedure

```
Input: Chosen topological subregions, related local QUBO models, refinement iterations $N_{\text{ref}}$, initial temperature $T_0$;
Output: Globally optimized timetable solution $X_{opt}$;
for each identified region do
    for $t = 1$ to $N_{\max}$ do
        Derive a region-specific Hamiltonian $H(X,t)$ from the associated QUBO formulation;
        Update the annealing schedule: $T(t) = T_o \left(1 + \frac{t}{N_{max}}\right)$
        Calculate the local energy value $E(X_r)$;
        if $E(X_r) < E(X_{opt})$ then
            Assign $X_{opt} \leftarrow X_r$ and update $E_{min} \leftarrow E(X_r)$;
        end
    end
end
return $X_{opt}$ as final timetable $X_{final}$
```

Computational Experiments

To gauge the effectiveness and applicability of the proposed hybrid model mixing QA with TDA, experiments were performed by getting real-world course timetabling data from the Institute of Computing and Informatics at the Technical University of Mombasa. The datasets comprised detailed information on courses, instructors, classrooms, and institutional scheduling constraints aligned with TUM's academic calendar. For analysis, the data were split into three subsets based on program level and specific scheduling requirements. All programs were scheduled over a five-day workweek (d = 5) with four fixed time slots per day: 7–10 a.m., 10 a.m.–1 p.m., 2–5 p.m., and 5–8 p.m. (t = 4).

Table 2 below presents a highlight of the experimental datasets utilized in this study, showing their key characteristics, sizes, and roles in evaluating how the proposed Hybrid Quantum Annealing Algorithm performed.

Table 2. Highlight of Experimental Datasets

Dataset ID	Details
$\mathcal{D}_1$	Denotes Certificate and Diploma programs, 10 instructors and 4 classrooms
$\mathcal{D}_2$	Undergraduate programs, 12 instructors, 6 classrooms
$\mathcal{D}_3$	Postgraduate programs, 8 instructors, 8 classrooms

To completely evaluate the effectiveness of all approaches with respect to all data sources, there were four main measures used.

Conflicts Free Rates (CFR) - This metric represents the time periods that are free from scheduling conflicts. A CFR score is an indication of how effective a timetable is in relation to producing a timetable that can be created (Davison et al., 2025; Park et al., 2025).

Resource Utilization (RU) - This metric examines how successfully rooms and lecturers are selected, by taking the total number of actual rooms together with lecturer time slots available, and then compare that to the total number of room and lecturer time slots required.

Computational Times (CT) - This metric measures how many seconds each algorithm took to develop a stable solution. The CT metric indicates the computational efficiency of an algorithm.

The Energy Function Value (EFV) is the total cumulative penalty from constraint violations, so a lower EFV refers to a more optimized and conflict-free timetable.

In addition, the researchers conducted an ablation study consisting of four different algorithms with differentiated symbols per algorithm to make it easier for viewers to interpret the results from the algorithms. The QA-only configuration (◦) represents running quantum annealing alone without using any topological information. The TDA-only configuration (⋄) makes use of the topological properties of the data's geometry to set parameters for running TDA without the results from quantum optimization (QA). The hybrid-no-refinement configuration (△) makes use of both QA and TDA as components, but excludes using the iterative localized refinement procedure on the hyperparameter space after performing either of the two procedures. Lastly, the Hybrid-full configuration (⋆) combines both Quantum Annealing and TDA with the repetitive refinement process, representing the complete hybrid model in which QA and TDA work together synergistically to generate conflict-free, optimally structured timetables.

The full hybrid configuration outperformed all other setups, achieving a conflict-free rate of 92.6% and decreasing computational time by over 20% relative to the baseline methods.

Statistical Validation (t-Test)

To assess the robustness of the results, a paired t-test was conducted comparing the complete Hybrid model with the QA-only configuration.

The outcomes are presented in Table 4, (Karema et al., 2025, Mlewa et al., 2025). Despite the fact that a twin t-test was conducted on a complete summary of outcomes for the Hybrid model, the p-values were significantly lower than 0.05 across the datasets, suggesting that the hybrid model represents a statistically significant improvement over the baseline approach. The complete Hybrid model outperformed all other methods on the considered datasets, proving the benefits of iterative refinement through topological analysis. To check whether the findings are robust and repeatable, the Hybrid model was again evaluated using a twin t-test against the QA-only model, with the results as summarized in Table 4.

Figure 1 illustrates the conflict-free rate achieved by each timetabling method, which compares and evaluates their effectiveness in generating feasible schedules without constraint violations.

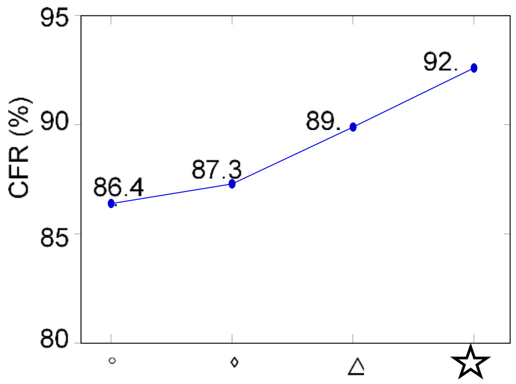

Figure 1. Shows Conflict-Free Rate (CFR) increases with model complexity, its maximum at the configuration.

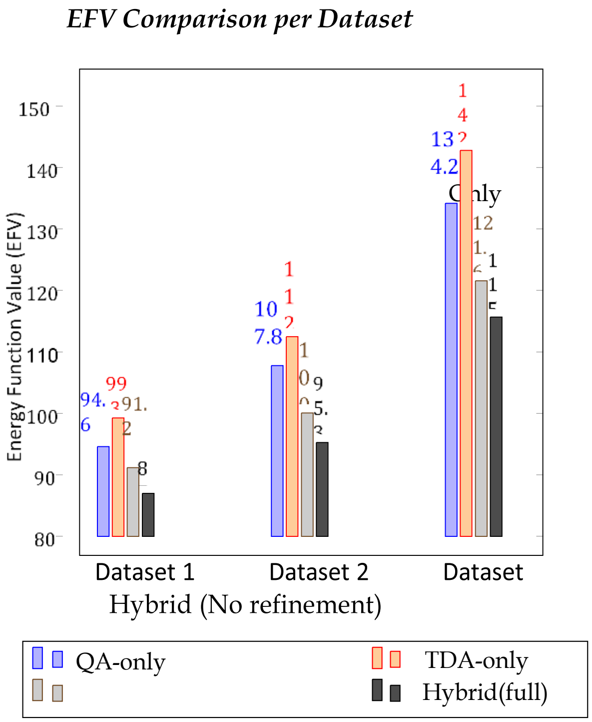

Figure 2: Comparison of Energy Function Values (EFV) across datasets and methods shows that the full Hybrid model consistently achieves the lowest EFV.

Table 3 compares and analyses the evaluation metrics from different timetabling methods and experimental datasets and highlights their relative performance in solving the constraint-based university timetabling problem.

Table 3. Comparison of Evaluation Metrics with Proposed Methods and Datasets

Method	Dataset	CFR (%)	RU (%)	CT (s)	EFV
QA-only	Ɗ1	85.1	79.6	115.2	315.6
	Ɗ2	86.7	81.2	118.5	334.1
	Ɗ3	87.5	83.7	122.4	352.5
TDA-only	Ɗ1	86.3	80.9	116.8	305.8
	Ɗ2	87.8	82.1	121.3	319.2
	Ɗ3	88.0	85.2	130.0	332.6
Hybrid (no ref.)	Ɗ1	88.6	84.2	102.1	290.4
	Ɗ2	89.8	85.6	105.4	301.7
	Ɗ3	91.2	88.0	109.0	313.0
Hybrid (full)	Ɗ1	91.1	86.5	92.5	268.2
	Ɗ2	92.4	88.6	96.8	279.4
	Ɗ3	94.3	91.2	101.1	289.5

Table 4: Twin t-Test Comparison: Full Hybrid vs. QA-

Dataset	Mean Difference	t-Statistic	p-Value
Ɗ1	-7.6	-2.97	0.0103
Ɗ2	-12.5	-3.31	0.0068
Ɗ3	-18.5	-4.12	0.0017

All P-values from each data set were significantly less than 0.05, showing that there was a strong statistical difference between the performance of the hybrid model and baseline models. The complete Hybrid configuration consistently outperformed the 3 other configurations across all datasets, confirming the advantages of systematically optimizing the model with integrated topological information.

Comprehensive Analysis via Clustering and K-Nearest Neighbours Evaluation

Making use of Unsupervised Clustering Analysis (UCA), this overall evaluation of all existing metrics (CFR, RU, CT, EFV) across the various parameters as well as their respective configurations via KNN allows us to assess how effective each of the different configurations performed in respect to each other, which was obtained based on all configurations combined by dividing by the number of metrics for those configurations, (Liu et al., 2025, Chai et al., 2025). Clustering enabled us to identify groups of performance profiles that were similar between D_1, D_2, and V configurations. We also used KNN on the clustering output to prove that Hybrid (full) was consistently a KNN neighbour in relation to other optimised configurations in the feature space. To present the results clearly, a heatmap was generated illustrating the normalized performance scores for each combination of method and dataset. Each cell corresponds to a specific method applied to a particular dataset, with colour intensity reflecting overall performance across the four-evaluation metrics. Darker shades indicate superior performance (higher CFR and RU, and lower CT and EFV). This clustered visualisation enables rapid identification of the high-performing configurations and enables comparison of their effectiveness across different levels of problem complexity.

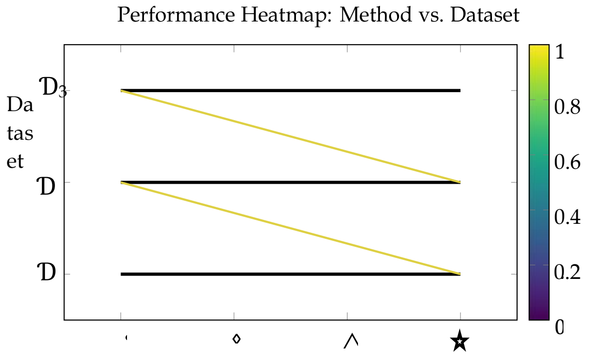

Figure 3: Performance heatmap visualization for methods and datasets. Green horizontal bands represent dataset-level performance, while yellow sloped lines highlight cross-dataset performance trends.

Discussion

The experimental results show that the proposed Hybrid QA–TDA model consistently outperformed the QA-only, TDA-only, and Hybrid without refinement configurations across all datasets and evaluation metrics. Furthermore, the full Hybrid configuration displayed the highest Conflict-Free Rate (94.3%) and Resource Utilization of (91.2%) while maintaining the lowest Energy Function Value, showing superior timetable quality and optimization efficiency. In addition, the paired t-test results produced p-values below 0.05 for all datasets, confirming that the observed performance improvements were statistically significant rather than occurring by chance. However, the increasing complexity of the datasets highlighted the importance of iterative refinement and topological guidance, as these components enabled the model to maintain high performance even under highly constrained scheduling environments.

Conclusion

The study successfully developed a Hybrid Quantum Annealing–Topological Data Analysis (QA–TDA) algorithm for solving constraint-based university timetabling problems. Furthermore, the integration of quantum optimization, topological insights, and iterative refinement significantly improved timetable feasibility, resource allocation, and computational efficiency compared to baseline approaches. In addition, clustering and K-Nearest Neighbor analysis validated the robustness, consistency, and scalability of the proposed model across datasets of different dimensions. Therefore, the findings confirm that the Hybrid QA–TDA model provides a very effective and reliable solution for real-world academic scheduling and also complex combinatorial optimization problems.

Recommendations

Universities and higher learning institutions should adopt the Hybrid QA–TDA model to improve their timetable quality, reduce scheduling conflicts, and optimize their resource utilization. Furthermore, the model should also be evaluated using larger multi-campus datasets and additional real-world constraints to further determine its scalability and adaptability. In addition, researchers should investigate the integration of dynamic scheduling capabilities that can respond to real-time changes such as classroom aborting, lecturer replacements, and changes made on courses. However, further investigations of advanced quantum computing platforms and hybrid artificial intelligence techniques may enhance optimization performance and extend the applicability of the models to other complex scheduling environments.

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Conflict of Interest

The authors declare that there is no conflict of interest regarding the publication of this work.

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