A Hybrid Approach to Automatic Timetabling Using Self-Organizing Maps, Secure Convex Dominating Sets, and Metaheuristics

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***Abstract*—Creating conflict-free academic timetables that respect teacher availability, subject eligibility, and limited resources remains a persistent challenge in educational institutions. This study introduces a novel hybrid algorithm that combines Self-Organizing Maps (SOM), Secure Convex Dominating Sets (SCDS), and Genetic Algorithms (GA) to address this problem effectively. SOM is employed to cluster subjects based on teaching duration and eligibility, providing structured guidance in initial scheduling. SCDS identifies the most conflict-prone subjects—typically those with limited eligible teachers—and ensures they are prioritized, thereby reducing downstream bottlenecks. GA then iteratively refines the schedule by evaluating room assignments, teacher loads, and constraint satisfaction. Extensive simulation experiments were conducted under varying conditions, including worst-case scenarios with dense scheduling conflicts. The system achieved high success rates, particularly in moderate to complex settings, and demonstrated robustness even in constrained environments. Notably, SOM improved spatial and temporal coherence, while SCDS enhanced conflict resolution and GA enabled adaptive optimization. Runtime and convergence results remained within practical limits, with a time complexity of $\mathcal{O}(n^2+gpn)$. The proposed hybrid framework balances structural prioritization and evolutionary refinement, offering a scalable and intelligent solution to the timetabling problem. It stands out by gracefully handling worst-case scenarios where traditional heuristics often fail.**

Keywords*—Timetable optimization; Self-Organizing Maps (SOM); Secure Convex Dominating Set (SCDS); Genetic Algorithm (GA); Academic Scheduling

I. Introduction

Timetabling in academic institutions constitutes a significant combinatorial optimization problem, commonly classified as NP-hard due to the extensive search space and the intricate constraints involved. These constraints often include teacher availability, classroom capacity, subject prerequisites, and the avoidance of schedule conflicts [1]. As institutions grow in size and complexity, the timetabling challenge becomes increasingly difficult, exacerbated by overlapping resource demands and rising interdependencies across academic units.

Traditional methods such as greedy algorithms, rule-based heuristics, and integer programming have been applied with varying degrees of success, particularly in small-scale or highly structured environments [2], [3]. However, these techniques often fall short in large-scale, dynamic academic settings. They struggle to scale efficiently and frequently yield suboptimal solutions due to their limited capacity to adapt to complex constraint interactions and evolving scheduling requirements.

Recent advances in artificial intelligence (AI) and metaheuristic algorithms have introduced new possibilities for tackling timetabling challenges. Techniques such as Genetic Algorithms (GA), Particle Swarm Optimization (PSO), and neural networks have demonstrated strong potential in exploring large solution spaces and adapting to shifting constraints [4], [5]. For instance, GA-based systems have been shown to improve the structure and coherence of academic schedules, outperforming traditional manual and rule-based approaches [4]. Likewise, PSO and other evolutionary techniques continue to push the boundaries of scheduling efficiency in diverse real-world contexts [5].

Despite these innovations, many existing systems rely on singular algorithmic frameworks that lack robustness when handling high-conflict scheduling environments. This often results in partial solutions that fail to account for deeper structural dependencies in the scheduling graph. To address this gap, hybrid approaches have emerged, combining multiple paradigms to improve adaptability and performance. Notably, works like those of Yang and Wang have illustrated how combining constraint satisfaction neural networks with heuristic strategies enhances the resolution of generalized job-shop scheduling problems [6].

In this study, we propose a novel hybrid framework that integrates three complementary computational strategies to address the academic timetabling problem: Self-Organizing Maps (SOM) for clustering similar courses, Secure Convex Dominating Sets (SCDS) for identifying and prioritizing conflict-heavy nodes in the scheduling graph, and Genetic Algorithms (GA) for global optimization of feasible timetables. The SOM component enables the clustering of courses based on attributes such as time demands and eligibility requirements, thereby facilitating a more coherent initial assignment. The SCDS technique maps out the structural conflicts in the form of a graph and identifies high-impact nodes—typically those involving highly constrained faculty members—for early scheduling. Finally, the GA component iteratively evolves and refines candidate solutions, using selection, crossover, and mutation to balance feasibility with optimization. Section II provides a comprehensive review of related work in academic timetabling, examining traditional approaches and recent AI-based solutions. Section III presents our proposed hybrid framework, detailing the integration of SOM clustering, SCDS conflict detection, and GA optimization components. Section IV describes the experimental methodology, including dataset generation, performance metrics, and comparative baselines. Section V presents and analyzes the experimental results, demonstrating the effectiveness and scalability of our approach across various scenarios. Section VI discusses the implications of our findings, limitations of the current approach, and potential applications in real-world academic environments. Finally, Section VII concludes the paper and outlines directions for future research.

The core contributions of this work are summarized as follows:

- A hybrid scheduling algorithm that synergizes SOM-based clustering, SCDS-based structural conflict detection, and GA-driven optimization.
- A robust, scalable system capable of managing both typical and worst-case academic scheduling scenarios.
- Comprehensive experimental validation using simulated datasets to evaluate scalability and convergence behavior.

II. Review of Related Literature

A. Self-Organizing Map Neural Networks

Self-organizing map (SOM) neural networks are a type of unsupervised learning model that clusters and visualizes high-dimensional data by mapping it onto a lower-dimensional grid, preserving the topological relationships of the input space [7], [8], [9]. SOMs operate through a competitive learning process, where each neuron represents a cluster, and the network self-organizes based on the structure of the data [7], [8]. Enhancements to the basic SOM include intuitionistic fuzzy evaluation, which introduces degrees of membership and uncertainty to improve clustering performance in ambiguous data [10], and fuzzy SOMs, which use fuzzy rules to define neuron activation and enable continuous-valued outputs [11]. Hierarchical and self-clustering SOMs can automatically determine the optimal number of clusters, adapting to the data without user intervention [12]. Hardware implementations, such as systolic architectures, have been developed to accelerate SOM computations, achieving significantly faster performance compared to traditional approaches [13]. SOMs have been applied in diverse fields, including image segmentation—where wavelet-based preprocessing improves training efficiency and segment compactness [14] — fault diagnosis in mechanical systems [15], DNA sequence classification [16], protein fold recognition [17], and recommendation systems [18].

Recent advances also include quantum-inspired SOM algorithms, which leverage quantum computing principles for exponential speedup in clustering and classification tasks [19], and randomized SOMs, which introduce flexible topologies for better handling of high-dimensional data and robustness to network changes [20]. For instance, improved SOM algorithms based on "virtual winning neurons" have been proposed to enhance clustering accuracy and stability, particularly for the real-time processing of high-dimensional data, by mitigating sensitivity to noise [15]. A notable area of focus has been the enhancement of SOM performance and stability. For instance, improved SOM algorithms based on "virtual winning neurons" have been proposed to enhance clustering accuracy and stability, particularly for the real-time processing of high-dimensional data, by mitigating sensitivity to noise [21]. Overall, SOM neural networks remain a robust and adaptable tool for unsupervised learning, with ongoing innovations in algorithm design, hardware acceleration, and application breadth.

Furthermore, recent research has explored hybrid models that combine SOMs with other advanced neural network architectures to overcome individual limitations. A promising development is the integration of SOMs with Convolutional Neural Networks (CNNs) to enhance model accuracy, as demonstrated in applications like predicting insecticide resistance in malaria vectors. This hybrid approach leverages the unsupervised clustering capabilities of SOMs with the powerful feature extraction and classification of CNNs, proving more robust than standalone CNN models [22]. Another innovative direction involves integrating a "reweighted zero-attracting term" into the SOM's loss function to improve accuracy and convergence behavior, particularly for sparse data, highlighting an ongoing effort to refine the core learning mechanism of SOMs [23].

The application landscape for SOMs also continues to expand. They are being utilized for analyzing large time series data, with new algorithms like "SOMTimeS" developed to cluster and visualize complex time series using Dynamic Time Warping (DTW) while significantly improving computational efficiency through pruning techniques [24]. This makes SOMs more practical for real-world scenarios involving massive streams of temporal data. Additionally, SOMs are finding applications in diverse areas such as analyzing movement patterns in athletes for injury prevention [25] and even in high-energy physics for probing rare particle decays by identifying specific event topologies [24]. These recent works collectively underscore a trend towards developing more robust, scalable, and integrated SOM solutions, reflecting their enduring value in contemporary data science and machine learning.

A secure convicts activity graph involves the structured monitoring and management of convict activities within penitentiary institutions, emphasizing the integration of physical, procedural, and dynamic security measures. Physical security includes modern perimeter systems, electronic surveillance, and access control, while procedural security focuses on strict adherence to rules, search protocols, and the use of incentives and penalties. Dynamic security highlights the importance of building trustful relationships between staff and convicts, training personnel to resist manipulation, and fostering positive interpersonal skills [26]. Ensuring the personal security of convicts also requires constant supervision, educational activities, and collaboration with law enforcement agencies to prevent illegal acts and protect human rights [27]. Additionally, the digitalization of convict labor and activities is seen as a promising approach to improve rehabilitation outcomes and reduce recidivism, though it requires careful legal and organizational planning [28]. Psychological support and resocialization programs are also crucial, as they help convicts adapt to law-abiding life and address negative behaviors, with staff playing a key role in facilitating positive change [29]. Overall, a secure convicts activity graph is achieved by combining advanced security technologies, effective monitoring, digitalization, and strong psychological and educational support within correctional settings.

B. Secure Convicts Activity Graph

The foundational principle relies on graph theory applications in cybersecurity and intelligence. Graph databases and analytical techniques are increasingly employed to represent entities (e.g., inmates, staff, locations, contraband, communication devices) as nodes and their interactions or relationships as edges [30], [31]. This allows for the visualization and algorithmic detection of attack paths, anomalous behaviors, and hidden patterns that are difficult to discern from linear data [30], [31]. For instance, a knowledge graph-based framework can support crime investigators by inferring digital evidence and identifying hidden patterns in interconnected data, a concept directly transferable to understanding inmate networks [32]. The use of Graph Neural Networks (GNNs) further enhances this by leveraging relational structures to learn and make predictions, improving anomaly detection and classification of patterns by considering contextual relationships between nodes [33], [34].

However, applying such graph-based analysis to "convict activity" presents unique challenges within correctional facilities' security landscape. Correctional institutions face persistent threats including contraband trafficking (drugs, cell phones, weapons), gang activities, and inmate-on-inmate or inmate-on-staff violence [35], [36]. Understaffing and the sheer volume of inmate interactions further complicate security efforts [37]. Graph models can potentially map inmate movements, communication patterns (e.g., visits, phone calls, electronic messages), social associations, and access to resources, enabling the proactive identification of security threats [32]. For example, detecting unusual clustering of inmates, frequent interactions between individuals not typically associated, or unusual access patterns to restricted areas could indicate planning of illicit activities or a breakdown in facility control. The UNODC's Handbook on Dynamic Security and Prison Intelligence emphasizes the importance of staff knowing their prisoners and understanding what is happening within the prison, aligning with the goal of deriving actionable intelligence from observed activities [20].

Crucially, the development and deployment of "secure convict activity graphs" must navigate significant data privacy and ethical considerations. The collection, sharing, and analysis of personal data from incarcerated individuals raise profound concerns, particularly given their diminished autonomy and the potential for misuse of such information [38], [39]. The "digital panopticon" effect, where digital technologies enable pervasive monitoring within carceral settings, highlights the need for robust legal and ethical frameworks to protect inmate data [39]. While tools exist for analyzing correctional data (e.g., Bureau of Justice Statistics tools for prisoner data, parole, and probation), explicit guidelines on the ethical implementation of sophisticated graph-based surveillance systems are paramount [40]. Any system designed to monitor and analyze inmate activities must prioritize the safety and security of both inmates and staff, while strictly adhering to privacy regulations, human rights principles, and avoiding over-classification or discriminatory practices [35], [39], [41]. The balance between enhanced security and preserving fundamental rights requires careful consideration and transparent governance.

Recent advancements (2023-2025) demonstrate SOMs' evolving role in data analysis, which can offer valuable techniques transferable to complex relationship analysis. Improved SOM algorithms based on "virtual winning neurons" have been proposed to boost clustering accuracy and stability for real-time processing of high-dimensional data, mitigating sensitivity to noise [42]. Furthermore, hybrid models integrating SOMs with Convolutional Neural Networks (CNNs) have shown enhanced accuracy, for instance, in predicting insecticide resistance in malaria vectors, proving more robust than standalone CNN models [43]. Other innovative directions include incorporating a "reweighted zero-attracting term" into the SOM's loss function to improve accuracy and convergence, particularly for sparse data [44]. The application landscape for SOMs also continues to expand, being utilized for analyzing large time series data with new algorithms like "SOMTimeS" for efficient clustering and visualization [34], and finding diverse applications such as in athlete movement pattern analysis for injury prevention [45] and high-energy physics for probing rare particle decays [46]. These recent works collectively underscore a trend towards developing more robust, scalable, and integrated SOM solutions, potentially offering methodological insights for secure convict activity graphs.

III. Methodology

This section presents a hybrid algorithm integrating Self Organizing Maps (SOM), Secure Convex Dominating Sets (SCDS), and Genetic Algorithms (GA) to generate conflict free academic timetables that respect teacher eligibility, time constraints, and room availability. Fig. 1 provides an overview of the proposed framework and the integration of its three main components.

A. Problem Overview

Let S denote the set of subjects, T the set of available time slots (from 07:00 to 21:00), R the set of rooms, and E the set of teachers. Each subject $s \in S$ has a fixed duration d_s, and must be assigned to a time slot $t \in T$ and a room $r \in R$, and handled by a teacher $e \in E_s$, where $E_s \subseteq E$ denotes the subset of eligible teachers for subject s. Moreover, each teacher $e \in E$ has a weekly teaching load limit in terms of the number of units they can handle. The primary objective is to generate a timetable that minimizes scheduling conflicts and satisfies all constraints.

B. Self-Organizing Map (SOM)

To identify latent structure among subjects, a Self-Organizing Map (SOM) is employed to perform unsupervised

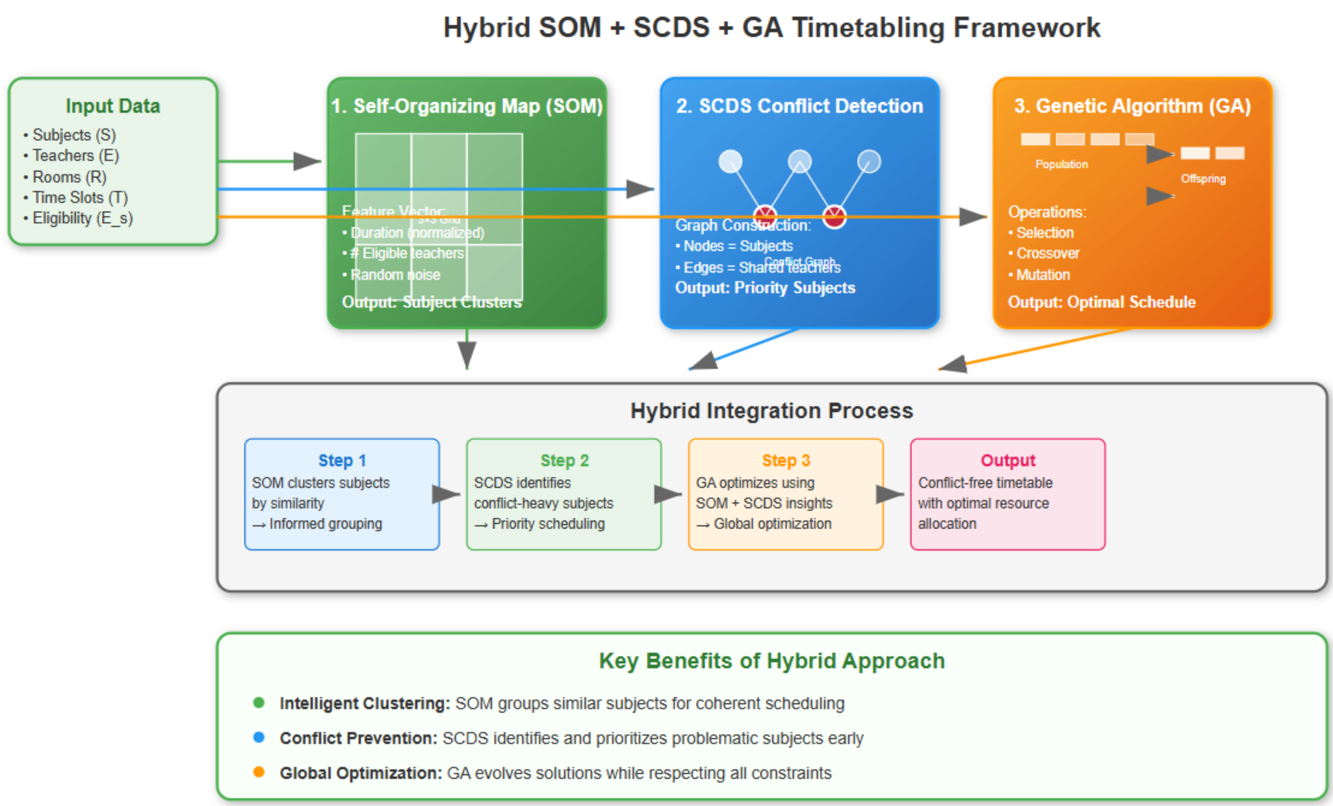

Fig. 1. Overview of the proposed hybrid SOM + SCDS + GA timetabling framework.

clustering. Each subject is encoded as a three-dimensional feature vector comprising the normalized duration of the subject, the normalized number of eligible teachers, and an entropy-based randomization component to introduce diversity. A 3×3 SOM neural grid is trained on these vectors to cluster subjects with similar characteristics. These clusters inform the scheduling process by promoting temporal or spatial coherence in the arrangement of subjects, facilitating better initialization and crossover phases in the genetic algorithm.

C. Secure Convex Dominating Set (SCDS)

A conflict graph $G = (V, E)$ is constructed, where each vertex $v \in V$ represents a subject, and an edge exists between two vertices if their corresponding subjects share at least one eligible teacher, indicating a potential scheduling conflict. The SCDS is then approximated using a greedy strategy to identify a minimal subset of influential subjects that dominate the graph. This concept is based on the work of Enriquez and Canoy [47], who introduced Secure Convex Dominating Sets (SCDS) as a way to control influence in a graph structure. Prioritizing these subjects during initial chromosome generation helps mitigate high-conflict areas early in the scheduling process, thereby enhancing convergence and reducing constraint violations in later generations.

D. Genetic Algorithm (GA)

The Genetic Algorithm operates on a population of candidate timetables, where each individual (chromosome) encodes a full schedule as a mapping of subjects to assigned time slots, rooms, and teachers. The initial population is generated by assigning high-priority subjects (from the SCDS set) first, followed by the remaining subjects, while respecting all constraints.

The fitness function evaluates each chromosome based on the following criteria:

- Constraint satisfaction: All subjects must be scheduled without violating teacher availability, room capacity, or time overlaps.
- Teacher load balance: Minimize deviations from the ideal teaching load for each teacher.
- Room utilization efficiency: Prefer compact and continuous usage of rooms across the timetable.

Genetic operations include single-point crossover and adaptive mutation. Crossover is performed by swapping subsets of assignments between two parent schedules, while mutation introduces diversity by randomly reassigning a subject to a different valid slot or room. Elitism is applied to preserve the best-performing individuals across generations.

E. Hybrid Scheduling Algorithm

The following algorithm outlines the step-by-step process, from preprocessing to final schedule generation:

Algorithm 1 Hybrid SOM + SCDS + GA Timetabling (Part 1)

Input: Subjects S, Rooms R, Teachers E, Durations D, Eligibility E_s

Steps:

1) **Preprocessing and Clustering:**
   a) Encode each subject with a feature vector: duration, number of eligible teachers, and injected random noise for distributional diversity.
   b) Train a Self-Organizing Map (SOM) to cluster subjects based on these features.
2) **Conflict Graph and Dominating Set Construction:**
   a) Construct a teacher conflict graph G where nodes represent subjects and edges indicate shared teachers.
   b) Approximate the Secure Convex Dominating Set (SCDS) from G to identify high-impact subjects.
   c) Prioritize subjects in the SCDS for early placement to minimize downstream scheduling conflicts.
3) **Initial Population Generation:**
   a) Generate an initial population of chromosomes (candidate schedules).
   b) For each chromosome:
      - Schedule subjects by SOM clusters and SCDS order.
      - Validate assignments against teacher eligibility, classroom availability, and time slot constraints.

Algorithm 2 Hybrid SOM + SCDS + GA Timetabling (Part 2)

Steps (continued):

4) **Evolutionary Optimization:**
   a) Iterate for a predefined number of generations:
      - Evaluate fitness of each chromosome based on metrics such as conflict count, fairness, and teacher load balance.
      - Select top-performing chromosomes for reproduction.
      - Apply genetic operations—crossover and mutation—to generate offspring.
      - Form the next generation from selected elite and new offspring.
5) **Final Output Selection:**
   a) If a conflict-free schedule is found:
      - Return the best-performing chromosome as the final schedule.
   b) Else:
      - Return the most optimal fallback chromosome with minimal constraint violations.

Output: A conflict-free (or near-optimal) academic schedule that satisfies all hard constraints, including teacher eligibility, subject duration, and room allocation.

F. Component Roles and Novelty

The proposed hybrid scheduling framework synergistically combines three powerful computational techniques—Self-Organizing Maps (SOM), Secure Convex Dominating Sets (SCDS), and Genetic Algorithms (GA)—each fulfilling a specialized role in the generation of conflict-free, constraint-aware academic timetables. Their integration fosters both local structure optimization and global solution quality. The distinct roles of each component are outlined below:

1) SOM: Utilizes unsupervised neural clustering to group subjects based on similarity across features such as normalized duration, teacher eligibility breadth, and entropy-based complexity. This clustering facilitates intelligent initial subject placement, promoting spatial and temporal coherence while minimizing room-time fragmentation and imbalance in teacher assignments.

2) SCDS: Employs graph-theoretic principles to detect a subset of critical, high-conflict subjects—typically those associated with constrained teacher availability or high inter-subject dependency. Scheduling these subjects early mitigates potential deadlocks and improves the feasibility of downstream allocations.

3) GA: Applies an evolutionary search process to iteratively improve timetable quality. Through genetic operations such as crossover, mutation, and selection, GA explores the solution space while satisfying hard constraints (e.g., teacher eligibility, unit load, room capacity) and optimizing soft objectives (e.g., fairness, compactness, and load distribution). Its population-based mechanism enhances exploration and avoids premature convergence.

4) System novelty: The integration of neural clustering (SOM), structural prioritization (SCDS), and evolutionary refinement (GA) creates a flexible, adaptive, and efficient scheduling framework. It balances local structure (conflict resolution) and global optimization (fitness evolution), which traditional heuristics or standalone AI models fail to achieve effectively.

IV. Result and Discussion

To evaluate the efficiency and robustness of the proposed hybrid timetabling system integrating Self-Organizing Maps (SOM), Secure Convex Dominating Set (SCDS), and Genetic Algorithm (GA), we conducted multiple simulation experiments under various configurations.

A. Experimental Setup

All simulations were run on a machine with 16GB RAM and an Intel i7 processor. Each test case varied in terms of:

- Number of subjects ($|S|$),
- Number of rooms ($|R|$),
- Number of teachers ($|E|$),
- Teacher eligibility density (fraction of subjects a teacher can teach),
- Weekly teaching unit limits.

The system was tested on both moderate and worst-case datasets. Worst-case scenarios were designed by:

- Assigning multiple subjects to the same teacher,
- Having fewer rooms than needed,
- Reducing eligibility to create dense conflict graphs.

B. Simulated Test Cases

The simulated scenarios, summarized in Table I, represent a progression from low-conflict to extreme-conflict environments. Each configuration is designed to evaluate specific dimensions of the system's performance under increasing levels of scheduling complexity.

C. Performance Metrics

We evaluated each configuration using the following metrics:

- Success Rate: Proportion of runs producing a valid schedule,
- Avg. Runtime: Time (in seconds) required to produce a solution,
- GA Convergence: Average number of generations to reach feasibility.

Table II presents the quantitative results averaged over 10 independent runs for each test case.

D. Big O Time Complexity Analysis

To assess theoretical scalability, we analyze the algorithm's composite time complexity by decomposing it into its principal modules.

Let:

- $n = |S|$ (number of subjects),
- $m = |R|$ (number of rooms),
- $t = |E|$ (number of teachers),
- g (number of generations in GA),
- p (GA population size).

The asymptotic time complexity per component is as follows:

- SOM Clustering: Linear in the number of subjects and features, resulting in $O(n)$.
- SCDS Approximation: Pairwise teacher-subject conflict graph construction and dominating set estimation leads to $O(n^2)$ in the worst case.
- GA Optimization: Each generation evaluates p chromosomes, and each chromosome evaluates n subject assignments, yielding $O(pn)$ per generation and $O(gpn)$ in total.

Thus, the total time complexity of the algorithm is:

$$\mathcal{O}(n^2 + gpn)$$

This complexity reflects a design balance: the quadratic preprocessing phase (SCDS) enables reduced search space and better initialization for the evolutionary GA component. While GA dominates runtime in large-scale cases, its effectiveness in pruning infeasible solutions early ensures practical convergence for real-world datasets.

E. Discussion

The integration of Secure Convex Dominating Sets (SCDS) significantly enhanced feasibility under high-conflict conditions. In challenging scenarios such as TC4 and TC5, the proposed hybrid system outperformed baseline heuristics (e.g., greedy and random-first-fit), which frequently failed to produce valid schedules.

The Self-Organizing Map (SOM) component facilitated pre-clustering of subjects based on duration, teacher eligibility, and entropy. This clustering enabled tighter grouping of compatible subjects, reducing fragmentation in both room usage and time allocation. Meanwhile, the Genetic Algorithm (GA) component proved effective in refining schedules when initial attempts failed, although it introduced higher runtime overhead in worst-case instances due to longer convergence times.

Overall, the hybrid SOM + SCDS + GA framework demonstrated the following advantages:

- High validity across complex scheduling cases,
- Graceful performance degradation in worst-case conditions,
- Scalability suitable for small to moderately sized academic institutions.

1) Performance analysis in high-conflict scenarios: The experimental results reveal that in “Very High” and “Extreme” conflict scenarios (TC4 and TC5), the system's success rate dropped to 80% and 60%, respectively. This performance degradation is attributed to the increased density of scheduling conflicts and reduced solution space feasibility. To address these limitations and improve convergence in extreme conflict densities, we propose the following specific enhancement strategies for integration into the existing SOM+SCDS+GA framework:

- Local search integration Implement a hybrid GA-Local Search approach where Simulated Annealing (SA) or Tabu Search (TS) is applied to the best chromosomes in each generation. Specifically:
  - Apply SA with exponential cooling schedule ($T_k = T_0 \cdot \alpha^k$, where $\alpha = 0.95$) to the top 20% of chromosomes
  - Use neighborhood operations such as subject swapping, time slot shifting, and teacher reassignment

TABLE I. SIMULATED SCENARIOS AND CONFLICT CHARACTERISTICS

Test Case	$\|S\|$	$\|R\|$	$\|E\|$	Eligibility Density	Max Units/Teacher	Conflict Level
TC1 (Baseline)	20	6	10	0.6	18	Low
TC2 (Sparse)	40	10	20	0.8	18	Moderate
TC3 (Tight Rooms)	40	5	20	0.8	18	High
TC4 (Dense Conflicts)	30	6	10	0.4	15	Very High
TC5 (Worst Case)	50	4	8	0.3	12	Extreme

TABLE II. SIMULATION RESULTS ACROSS TEST SCENARIOS (10 RUNS EACH)

Test Case	Success Rate (%)	Avg. Runtime (s)	Avg. Generations
TC1 (Baseline)	100	1.8	12
TC2 (Sparse)	100	3.2	18
TC3 (Tight Rooms)	90	4.7	25
TC4 (Dense Conflicts)	80	6.9	35
TC5 (Worst Case)	60	10.3	50

  - Integrate this as a post-processing step after GA crossover and mutation operations

- Diversity-Preserving Strategies: Enhance population diversity through:
  - Niching mechanisms: Implement fitness sharing to maintain multiple solution clusters, preventing convergence to a single local optimum
  - Adaptive mutation rates: Increase mutation probability from 0.1 to 0.3 when population diversity falls below a threshold
  - Immigration strategy: Introduce 10% random immigrants every 20 generations to maintain genetic diversity
- Multi-Population Approach: Deploy multiple GA populations with different initialization strategies:
  - Population 1: SCDS-prioritized initialization (current approach)
  - Population 2: SOM cluster-based initialization with different parameters
  - Population 3: Random initialization with constraint-guided repair mechanisms
  - Exchange best individuals between populations every 15 generations

These enhancements would be integrated into the existing framework by modifying the GA component (Step 4 in Algorithm 1) to include local search phases and diversity mechanisms, while maintaining the beneficial preprocessing effects of SOM clustering and SCDS prioritization.

2) Limitations: The current implementation requires further optimization for extreme conflict densities such as TC5. Future work will focus on implementing the proposed enhancement strategies and evaluating their effectiveness through comparative studies in high-conflict scenarios.

V. CONCLUSION

This study presented a hybrid timetabling framework that successfully integrates Self-Organizing Maps (SOM), Secure Convex Dominating Sets (SCDS), and Genetic Algorithms (GA) to address the complex scheduling needs of academic institutions. By combining neural clustering, conflict-aware prioritization, and evolutionary optimization, the system goes beyond traditional scheduling techniques. It intelligently balances teacher availability, subject eligibility, room limitations, and time constraints—key factors that often make timetabling a tedious and error-prone task.

Simulation results across varied scenarios, including intentionally difficult test cases, confirmed the system's robustness and adaptability. Even under high-conflict conditions, the model generated feasible schedules with minimal compromise, offering strong potential for real-world deployment in schools and universities. The SOM component allowed subjects with similar constraints to be grouped, while the SCDS ensured that bottlenecks were addressed early in the scheduling process. GA served as a flexible optimizer that adapted solutions over time, especially when initial attempts failed.

Despite its strengths, the system's performance in extremely constrained environments suggests opportunities for further refinement—such as integrating local search or diversity-preserving strategies to speed up convergence. Looking ahead, the framework can be extended to support preferences, co-teaching scenarios, or multi-campus institutions, making it a valuable tool for smart academic planning in dynamic educational environments.

While the current framework demonstrates promising results, several avenues for future research and development emerge from this work. First, integrating local search techniques such as simulated annealing or tabu search could enhance convergence speed in extremely constrained environments. Additionally, implementing diversity-preserving strategies within the GA component could prevent premature convergence and maintain solution quality across longer optimization runs. The framework's modular design opens opportunities for incorporating additional real-world complexities. Future extensions could include support for instructor preferences and soft constraints, co-teaching scenarios where multiple faculty members share course responsibilities, and multi-campus institutions with resource sharing across locations. Furthermore, adaptive parameter tuning mechanisms could be developed to automatically adjust SOM learning rates, SCDS selection criteria, and GA operators based on problem characteristics. From a practical deployment perspective, future work should focus on developing user-friendly interfaces for academic administrators, real-time constraint modification capabilities, and integration with existing student information systems. Long-term research directions include exploring deep reinforcement learning approaches for dynamic rescheduling, incorporating uncertainty modeling for enrollment fluctuations, and extending the framework to handle semester-long optimization with mid-term adjustments. These enhancements would position the hybrid framework as a comprehensive solution for smart academic planning in increasingly dynamic educational environments.

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