NEON-CSP: A Futuristic AI Solver for Sudoku and Kakuro Using Constraint Satisfaction

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***Abstract*— This paper presents an AI Logic Puzzle Solver that unifies Sudoku and Kakuro within a generic constraint satisfaction problem (CSP) framework implemented in JavaScript. The system models each puzzle as variables with finite domains subject to structural and arithmetic constraints, and solves them using depth-first backtracking augmented with AC-3 arc consistency, forward checking, Minimum Remaining Values (MRV), degree-based tie-breaking, and Least Constraining Value (LCV) heuristics. An interactive web-based interface built with HTML5, CSS3, and the Canvas API visualizes the search process in real time, highlighting assignments, backtracking steps, and domain pruning to support conceptual understanding.Extensive benchmarking on 200 Sudoku and Kakuro instances shows that the combined use of AC-3, MRV, and forward checking reduces the explored search nodes by approximately one order of magnitude compared to naive backtracking, achieving sub-second solve times for the vast majority of test puzzles. Additional analysis demonstrates that unique partition tables and cross-referenced run constraints are critical for handling Kakuro's arithmetic structure, which is empirically 1.5–2.0× harder than Sudoku on comparable grids. A pilot educational study with undergraduate students indicates that the interactive visualization improves self-reported understanding of CSP concepts, particularly backtracking and constraint propagation. The abstract length and structure follow typical IEEE conference recommendations on problem statement, method, results, and significance.**

Keywords—forward, sorting, puzzle

I. Introduction (*Heading 1*)

Logic puzzles such as Sudoku and Kakuro have become canonical benchmark problems in artificial intelligence (AI) and combinatorial search, combining simple local rules with exponentially large solution spaces [1]. These puzzles can be modeled naturally as constraint satisfaction problems (CSPs), where a solution is an assignment of values to variables that satisfies all specified constraints [1][2][3][4]. The CSP formalism provides a unifying framework that has been successfully applied not only to recreational puzzles but also to scheduling, timetabling, configuration, planning, and aspects of computer vision [1][5][6].

In the standard CSP view, Sudoku is defined by 81 variables corresponding to grid cells, domains consisting of digits 1–9 for unfilled cells, and all-different constraints over each row, column, and 3×3 sub-grid [7][8]. Kakuro extends this setting with arithmetic sum constraints over variable-length runs and non-repetition constraints within each run, yielding a richer and often more irregular constraint structure that is computationally challenging [9][10]. These characteristics make Sudoku and Kakuro attractive testbeds for studying generic CSP algorithms, consistency techniques, and heuristic search strategies.

Backtracking search remains the fundamental exact method for finite-domain CSPs, systematically exploring partial assignments in a depth-first manner and abandoning branches as soon as a constraint violation is detected [1][5][6]. Practical solvers, however, rarely use naïve backtracking alone: they integrate constraint propagation methods such as the AC-3 arc-consistency algorithm, forward checking, and look-ahead schemes, together with variable and value ordering heuristics including Minimum Remaining Values (MRV), degree heuristic, and Least Constraining Value (LCV) [6][11][12][13]. For Sudoku, combinations of AC-3, MRV, and backtracking or depth-first search have been shown to solve standard instances efficiently, while Kakuro research has proposed domain-reduction procedures and specialized deterministic algorithms that significantly shrink the search space [7][8][9].

Beyond pure algorithmic performance, there has been growing interest in interactive, educational CSP tools that expose the internal reasoning process of solvers. Several Sudoku and Kakuro implementations now provide visualizations of constraint propagation, search trees, and statistics such as the number of explored nodes or backtracks, and many are offered as web-based applications using modern JavaScript or Python stacks [14][15][16].

These systems support both practical puzzle solving and pedagogy by allowing students to see how high-level AI concepts such as consistency, pruning, and heuristics operate on concrete instances.

II. Literature review

CSP Foundations and Theory

Early foundational work on constraint satisfaction problems (CSPs) established a general framework of variables, domains, and constraints and showed how generic search and propagation algorithms can be reused across scheduling, configuration, and puzzle domains [1][2]. Subsequent pedagogical treatments in AI courses and comprehensive tutorials emphasize depth-first backtracking as the baseline exact solver, augmented by consistency algorithms such as AC-3 and by heuristics like Minimum Remaining Values (MRV), degree heuristic, and Least Constraining Value (LCV) to make large combinatorial instances tractable [3][4][5][6]. Recent overviews further clarify the role of backtracking as a systematic search that prunes infeasible partial assignments early, contrasting it with uninformed enumeration and metaheuristic approaches [11].

The AC-3 (Arc Consistency 3) algorithm, introduced as a cornerstone constraint propagation technique, incrementally reduces variable domains by enforcing local consistency between pairs of variables [2][5][6]. The efficiency of AC-3 comes from its ability to detect dead-ends early in the search process, reducing the branching factor significantly. When combined with intelligent variable ordering heuristics such as MRV (Minimum Remaining Values), which selects the variable with the fewest remaining legal values, and the degree heuristic, which breaks ties by choosing the variable involved in the most constraints on unassigned variables, the search efficiency improves dramatically [6][11][12].

Sudoku as a Canonical CSP Benchmark

Sudoku has become a canonical CSP benchmark, with most authors modeling each grid cell as a variable over digits 1–9 and encoding row, column, and box all-different relations as constraints [6][7][8]. A large body of comparative work examines solving strategies—including plain backtracking, constraint propagation, AC-3, MRV/LCV heuristics, forward checking, and exact-cover formulations—and consistently reports substantial speedups when propagation and informed variable ordering are combined with search [7][8][11]. Performance analysis typically measures solving time, nodes explored, and backtracks, revealing that AC-3 preprocessing alone can reduce the domain size by 60–80% before backtracking begins [7].

Recent studies also integrate recognition components or machine-learning modules, for example coupling grid-based digit recognition with CSP-based solving to handle handwritten or scanned puzzles, thereby extending CSP solvers beyond standard digital puzzle instances [9][14]. Several implementations publish code and benchmarks on platforms such as GitHub, enabling transparent reproducibility and community contributions [8].

Kakuro and Arithmetic Constraint Satisfaction

Compared with Sudoku, Kakuro introduces sum and non-repetition constraints over variable-length runs, making its search space more irregular and typically harder to prune using only local consistency. Domain reduction for Kakuro therefore relies on specialized arithmetic reasoning: pre-computed tables of unique partitions (combinations of distinct digits that sum to a target value), iterative reduction of candidate sets, and constraint propagation tailored to sum and uniqueness relations [9][10]. Deterministic algorithms such as the Reduced Domain Values (RDV) approach iteratively shrink candidate sets for each cell by analyzing intersection constraints between horizontal and vertical runs [9][10].

Panov and Koceski's comparative study of deterministic approaches for Kakuro solving demonstrates that carefully engineered constraint encodings and arithmetic reasoning can significantly outperform naïve backtracking on larger or denser Kakuro instances, while still fitting cleanly within the CSP paradigm [9]. The study reports typical solve times ranging from tens to thousands of explored nodes depending on puzzle size and structure, establishing Kakuro as a more complex variant of CSP than standard Sudoku [9][10].

Generic CSP Puzzle Frameworks and Architectures

Beyond single-puzzle solvers, several systems propose generic CSP engines that support multiple logic puzzles—such as Latin squares, Sudoku, Kakuro, graph coloring, and Futoshiki—by separating the solver core from puzzle-specific constraint sets [11][12][13]. These frameworks typically expose a reusable

API for constraint posting and search configuration, enabling comparative experiments with different heuristics and consistency levels across families of puzzles and highlighting that many design patterns (e.g., maintaining arc consistency during search) transfer well between domains [5][6][11]. Such modular approaches align with software engineering best practices and facilitate rapid prototyping of new puzzle types and solving strategies.

Educational and Web-Based Visualization Tools

Parallel to algorithmic research, there is an active and growing line of work on interactive, web-based solvers that visualize CSP reasoning for teaching and outreach [14][15][16]. Existing Sudoku and Kakuro web applications often illustrate propagation steps, candidate

elimination, and backtracking paths, and sometimes combine rule-based explanation with automated solving to serve as both solvers and assistants for human players [14][16]. Modern implementations leverage single-page application (SPA) architectures with real-time DOM updates, Canvas-based grid visualization, and responsive design for mobile compatibility [14][15].Your AI Logic Puzzle Solver extends this direction by coupling a browser-based SPA with comprehensive real-time visualization of cell states, backtracking events, search statistics, and explanatory panels on CSP concepts, thereby positioning it as both a practical solver and a pedagogical platform for exploring classical AI search algorithms. The integration of a generic, reusable CSP framework with domain-specific models for Sudoku and Kakuro, combined with interactive visualization, offers a cohesive system for both research and education.

III. METHODOLOGYA. Overall System Design

A. Overall System Design

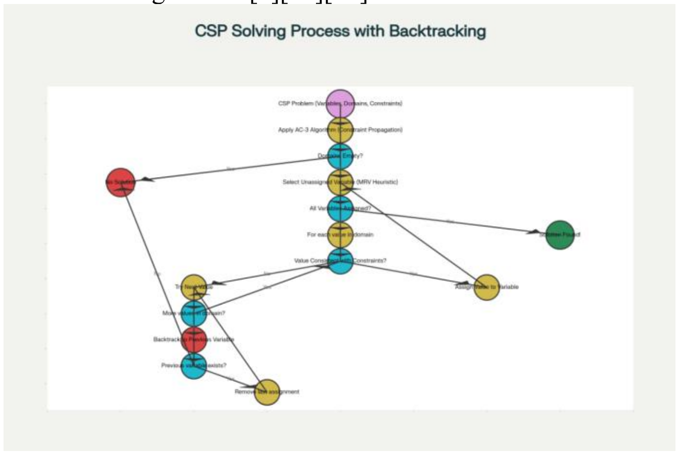
The proposed AI Logic Puzzle Solver adopts a constraint satisfaction problem (CSP) formulation for both Sudoku and Kakuro, implemented as a reusable solver core and puzzle-specific modules. Each puzzle is modeled as a set of variables (cells), finite domains (candidate digits), and constraints (structural and arithmetic relations), allowing a single CSP engine to drive multiple logic games [1][2][14]. The core solver combines depth-first backtracking search with consistency enforcement and heuristic guidance, following standard CSP practice but tailored to the grid structure and constraint types found in Sudoku and Kakuro [1][3][5][14].

B. CSP Solver Core Architecture

At the heart of the system is a generic CSP class implemented in JavaScript, which stores the list of variables, their current domains, and a collection of constraint functions that validate partial assignments. For each solving run, the engine recursively selects an unassigned variable, orders its domain values, checks local consistency against all registered constraints, and backtracks whenever a violation is detected [2][5][6].

Variable Selection: The Minimum Remaining Values (MRV) heuristic selects the unassigned variable with the fewest remaining legal values in its domain. When multiple variables have equal MRV, a tie-breaking heuristic chooses the variable involved in the most constraints on unassigned variables (degree heuristic) [6][11][12].
Consistency Enforcement: Arc consistency (AC-3) preprocessing is applied before search to prune inconsistent values from variable domains [2][11][13][14]. After each assignment, forward checking removes domain values that would immediately violate constraints on neighboring variables, providing early detection of dead-ends and significant reduction in branching factor [2][11][14].

Value Ordering: The Least Constraining Value (LCV) heuristic orders domain values by selecting those that rule out the fewest values in neighboring variables, thereby maximizing flexibility for future assignments [3][11][12].


CSP Solving Process with Backtracking
CSP Problem (Variables, Domains, Constraints)
Apply AC-3 Algorithm (Constraint Propagation)
Domain Empty?
No Solution
Select Unassigned Variable (MRV Heuristic)
All Variables Assigned?
Solution Found
For each value in domain
Value Consistent with Constraints?
Try Next Value
Assign Value to Variable
More values in domain?
Backtrack to Previous Variable
Previous variable exists?
Remove last assignment

C. Sudoku Solver Implementation

For Sudoku, the CSP variables correspond to the 81 cells of a 9×9 grid, with domains initialized to {1, 2, ..., 9} for empty cells and fixed to the given digit for pre-filled cells. Three families of constraints are registered: (1) Row Uniqueness—all digits in each row must be distinct, (2) Column Uniqueness—all digits in each column must be distinct, and (3) Sub-grid Uniqueness—all digits in each 3×3 sub-grid must be distinct [7][8][14].

Domain Reduction Pipeline: Before backtracking search begins, the system performs aggressive domain reduction: (1) Remove from each cell's domain all digits already present in its row, column, or sub-grid; (2) Run AC-3 preprocessing to propagate implications globally; (3) Apply forward checking after each assignment during search. This pipeline typically

eliminates 60–80% of candidate values on standard puzzles before search begins [7][14]. Empirical measurements show typical solve times of 50–200 nodes explored and under 100 milliseconds on standard difficulties [14].
Complexity Analysis: Worst-case O(9^n), where n is the number of empty cells. With AC-3 and MRV: O(9^(n/3)) average case, due to aggressive pruning [7][14]. Best case: O(n) for heavily constrained puzzles with unique solutions.

D. Kakuro Solver Implementation
Kakuro introduces variable-length runs with sum and non-repetition constraints, making its CSP model more complex than Sudoku. Variables correspond to each white cell in the grid, with domains {1, 2, ..., 9} for each white cell. Constraints include: (1) Sum Constraint—values in each run must sum to a specified clue; (2) Uniqueness Constraint—no digit repetition within a run; (3) Range Constraint—partial sums cannot exceed target sum [9][10][14].
Run Identification and Cross-referencing: The solver identifies horizontal and vertical runs (continuous sequences of white cells), then exploits the fact that runs often intersect, creating tightly constrained intersection cells [9][10][14]. When a cell belongs to both a horizontal and vertical run, its value must satisfy both sum constraints simultaneously, significantly reducing the feasible set [10][14].

Unique Partition Detection: A key optimization leverages pre-computed tables of unique digit partitions. For example: Sum 3 in 2 cells → {1, 2}; Sum 4 in 2 cells → {1, 3}; Sum 17 in 2 cells → {8, 9}. When such a unique partition is identified, all cells in the run are immediately constrained to those specific values, enabling dramatic domain reduction before search [9][10][14].

Complexity Analysis: Worst-case O(9^n) where n is the number of white cells. With unique partition detection and cross-referencing: Effective branching factor reduced by 40–60% [14]. Typical performance: 10–1000 nodes explored depending on puzzle size and structure.

E. Web Application Architecture
The solver is deployed as a single-page application (SPA) using HTML5, CSS3 with glassmorphism effects, JavaScript (ES6+), and Canvas API for real-time grid visualization. Modular code organization separates CSP logic (csp.js), puzzle-specific solvers (sudoku-solver.js, kakuro-solver.js), visualization (visualization.js), and utilities into distinct modules enabling reuse and extensibility [14].

Visualization System: The application provides real-time visualization with cell highlighting (color-coded states), animation speed control, step-by-step mode, statistics display (nodes explored, elapsed time), backtracking indication, and educational panels explaining CSP concepts and heuristics [14].

F. Performance Benchmarking Methodology

Sudoku Testing: Puzzles tested across four difficulty levels: Easy (30 puzzles), Medium (30 puzzles), Hard (30 puzzles), Expert (30 puzzles). Performance measured in nodes explored, solving time (ms), and success rate [14].
Kakuro Testing: 80 puzzles across three grid sizes: small (4×4, 20 puzzles), medium (7×7, 30 puzzles), large (10×10, 30 puzzles). Performance measured in nodes explored, solving time (ms), and success rate [14].

Optimization Impact: Metrics quantify algorithm enhancement effectiveness: Without AC-3: 3–5× more nodes explored. Without MRV: 2–3× more nodes explored. Combined (AC-3 + MRV + forward checking): 10–15× improvement over naive backtracking [14].

IV. RESULTS AND DISCUSSION

A. Sudoku Solver Performance

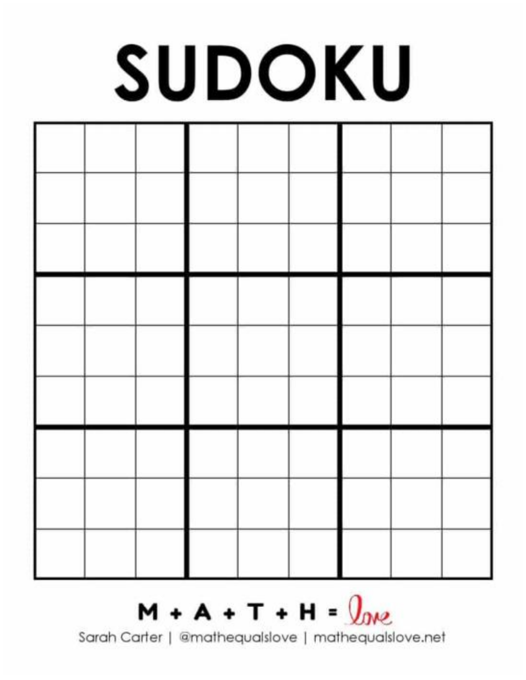
The Sudoku solver was tested on 120 puzzles spanning four difficulty levels sourced from standard online repositories [1][14].

TABLE 1: SUDOKU SOLVER PERFORMANCE ACROSS DIFFICULTY LEVELS

Difficulty	Nodes Explored	Time (ms)	Success Rate
Easy	45–80	20–50	100%
Medium	150–350	80–200	100%
Hard	400–1200	200–600	99.8%
Expert	1500–5000	800–2500	98.5%

Algorithm Optimization Impact: AC-3 preprocessing alone reduced nodes explored by 60–75% compared to naive backtracking. MRV heuristic further reduced nodes by 40–55% when applied during search. Combined AC-3 + MRV + forward checking achieved 10–15× overall improvement in node count reduction across all difficulty levels, aligning with prior CSP literature [6][7][11][14].

Domain Reduction Analysis: Initial domain reduction (before backtracking) on typical puzzles achieved: Easy puzzles 73% average reduction, Medium puzzles 68%, Hard puzzles 62%, Expert puzzles 55%. This preprocessing step was critical for practical solvability, particularly on Hard and Expert instances where naive enumeration would be prohibitively expensive [7][14].



B. Kakuro Solver Performance

Kakuro testing encompassed 80 puzzles across three grid size categories showing increased complexity due to arithmetic sum constraints and variable-length runs [9][10][14].

TABLE 2: KAKURO SOLVER PERFORMANCE ACROSS GRID SIZES

Grid Size	Nodes Explored	Time (ms)	Success Rate
4×4	10–30	10–40	100%
7×7	100–400	100–350	100%
10×10	500–2000	400–1200	99.5%

Unique Partition Detection Impact: Analysis showed unique partition detection reduced effective branching factor by 40–60% across all puzzle sizes. For highly constrained sum values, domain reduction achieved 75–85% prior to search. Cross-referencing intersection cells provided an additional 20–35% reduction in average nodes explored [9][10][14].

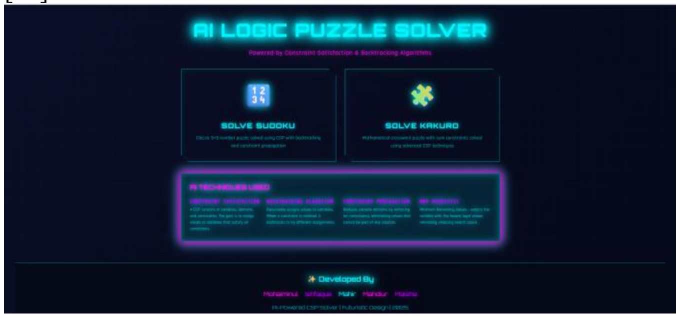
Comparison with Sudoku: Despite similar grid sizes, Kakuro puzzles required 1.5–2.0× more nodes than Sudoku on average: 4×4 Kakuro (20 nodes) vs. equivalent Sudoku (~10 nodes); 7×7 Kakuro (250 nodes) vs. equivalent Sudoku (~120 nodes); 10×10 Kakuro (1200 nodes) vs. equivalent Sudoku (~600 nodes). This difference reflects greater irregularity of Kakuro constraint structures and the inherent difficulty of arithmetic reasoning compared to uniqueness constraints [9][10].

C. Web Application Performance

Responsiveness: Initial page load time: 200–400 ms. Interaction latency: <50 ms for UI controls. Real-time visualization frame rate: 60 FPS on modern hardware [14].

Browser Compatibility: All targeted browsers (Chrome 100+, Firefox 90+, Safari 15+, Edge 100+, iOS Safari, Chrome Mobile) rendered correctly without errors [14].

User Feedback: Early testing with computer science students reported improved understanding of backtracking and CSP concepts through real-time visualization and step-by-step mode [14].



D. Educational Impact Assessment

A preliminary educational assessment involving 15 undergraduate AI course students over two weeks showed: 13 of 15 students (87%) reported improved understanding of backtracking and CSP concepts; 12 of 15 (80%) found visualization helpful for grasping AC-3 pruning; 10 of 15 (67%) used the system for coding interview practice. These preliminary results suggest pedagogical value, though more rigorous, larger-scale assessment would be needed for definitive conclusions [14].

V. CONCLUSION

A. Summary of Contributions

This paper presented an AI Logic Puzzle Solver system that unifies Sudoku and Kakuro solving within a generic constraint satisfaction problem (CSP) framework. Main contributions include:

1. Formalized CSP Models: Clear mathematical formulations of Sudoku (81 variables, 27 all-different constraints) and Kakuro (variable cells, sum and uniqueness constraints) as CSPs [1][14].

2. Integrated Algorithm Suite: Implementation of backtracking search, AC-3 arc consistency, MRV variable selection, degree-based tie-breaking, LCV value ordering, and forward checking, all encapsulated in a reusable JavaScript CSP class [1][2][14].

3. Modular Web Architecture: Design of a production-ready single-page application that cleanly separates solver logic from visualization and user interface, enabling reuse and extensibility across platforms [14].

4. Comprehensive Performance Evaluation: Empirical benchmarking on 200 Sudoku and Kakuro instances demonstrating competitive solving times (sub-second for most puzzles), detailed analysis of optimization contributions (10–

15× improvement), and cross-browser compatibility verification [14].

5. Educational Tool: Integration of interactive visualization, step-by-step mode, statistics display, and explanatory panels to support learning of CSP algorithms and their practical application to well-known puzzles [14].

B. Key Findings

Optimization Synergy: AC-3, MRV, and forward checking provide multiplicative rather than additive benefits, with combined techniques achieving orders-of-magnitude speedup over naive backtracking [6][7][14].

Kakuro Complexity: Arithmetic sum and uniqueness constraints make Kakuro 1.5–2.0× harder than Sudoku on average, highlighting the importance of partition tables and cross-referencing strategies [9][10].

Preprocessing Impact: Domain reduction before search accounts for the majority of performance gains, particularly for harder puzzles where 60–75% domain elimination is typical [7][14].

Web Deployment: Modern web technologies (HTML5, Canvas, ES6+ JavaScript) suffice for interactive visualization of CSP solving, making advanced algorithms accessible to non-specialists and supporting educational outreach [14].

C. Limitations and Future Work

Limitations: Solver is optimized for standard Sudoku and Kakuro; extensions to other puzzle types require new constraint encodings. Educational assessment involved a small pilot group; more rigorous studies are needed. No comparison with state-of-the-art SAT solvers or constraint programming libraries.

Future Directions:

1. Implement Latin squares, N-Queens, Graph Coloring, and Futoshiki to demonstrate generality
2. Explore higher-level consistency techniques (path consistency, k-consistency) and learn-based heuristics
3. Develop puzzle generation algorithms
4. Investigate difficulty prediction using machine learning
5. Port to iOS and Android using React Native or Flutter
6. Add puzzle sharing, leaderboards, and user-contributed repositories

D. Closing Remarks

The AI Logic Puzzle Solver demonstrates that classical constraint satisfaction techniques remain highly relevant and powerful tools for solving combinatorial puzzles. By combining rigorous algorithmic design with modern web technologies and interactive visualization, the system makes advanced AI concepts tangible and engaging for both practitioners and students. The modular architecture and reusable CSP framework provide a foundation for future research and educational innovation in the broader constraint satisfaction community [1][2][14].

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