

SOLVING CIRCUIT BOARD DRILLING TSP: A COMPARATIVE STUDY OF CPLEX AND TABU SEARCH METHODOLOGIES

Methods and Models for Combinatorial Optimization

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Table of contents

1. Overview	3
2. Part I: Exact Method Implementation	4
2.1. Problem description and mathematical formulation	4
2.2. Implementation with CPLEX	5
2.2.1. Core architecture	5
2.2.2. Instance generation framework	6
2.2.3. Data creation and problem solving	8
2.3. Computational results	9
2.3.1. Solution quality and optimality	9
2.3.2. Performance analysis	11
2.3.3. Scalability assessment	11
3. Part II: Tabu Search (TS) Implementation	12
3.1. Introduction	12
3.2. Algorithm design	13
3.2.1. Solution representation	14
3.2.2. Neighborhood structure	14
3.2.3. Memory structures	15
3.2.4. Search strategies	16
3.2.5. Implementation details	17
3.3. Parameter calibration	18
3.3.1. Calibration methodology	18
3.3.2. Parameter analysis	19
3.3.3. Computational performance metrics	19
4. Comparative analysis	20
4.1. Solution quality and runtime comparison	21
5. Conclusions	23
5.1. Implementation insights and recommendations	23
5.2. Future improvements	23
6. Appendix A - Compilation instructions	24
6.1. Windows	24
6.2. Linux	24

List of figures

Figure 2: Comparison of drilling paths for a 100x100mm board	22
Figure 3: Comparison of drilling paths for a 125x125mm board	22

List of Tables

Table 1: Computational performance across board sizes	10
Table 2: Computational performance metrics for different board sizes	11
Table 3: Parameter calibration insights for Tabu Search	19
Table 4: Performance metrics across problem sizes	20
Table 5: Computational efficiency comparison	21

1. Overview

The present report describes the comparison of the exact and heuristic optimization approaches to solve the Circuit Board Drilling Problem. More precisely, this is an NP-hard problem aimed at finding the best possible drilling sequence to minimize the total processing time because each hole is supposed to take equal time to drill.

- The *exact* approach relies on a mixed integer linear programming formulation, modeling the problem as a TSP on a weighted graph. Implementation is done by using the CPLEX solver. The heuristic approach makes use of a Tabu Search algorithm, which explores the solution space in an iterative way by using adaptive memory structures and smart search strategies.
- It includes small (50×50 mm), medium, and large (150×150 mm) boards with different component densities. For small and medium-sized instances, the MILP approach was able to find an optimum solution within reasonable time limits. However, for larger instances, it performed poorly owing to the exponential growth of the solution space.
- On the other hand, the Tabu Search algorithm proved to be much more scalable, since it provided high-quality solutions for large instances in a fraction of the time taken by the exact method. Dynamic tabu tenure, aspiration criteria, and strategic intensification and diversification mechanisms significantly improved the heuristic's performance.

Indeed, the relative comparison reveals that Tabu Search provides solutions within 5% from optimality for the small instances and maintains its solution quality advantage even for the largest instances, where the exact method was unable to find feasible solutions within the time limit. The performance of the heuristic is also robust over the different problem sizes, with solution times increasing much more gradually than those of the exact approach.

Based on these results, the report suggests that the exact method should be used for small instances of up to 50 holes and could be considered for medium-sized instances from 50 to 100 holes if solution quality is of paramount importance. It strongly recommends the Tabu Search approach for large instances over 100 holes and in time-critical production environments due to its superior scalability.

Both parts of the assignments share the same logic to create the instances to solve the respective problem in specific folders as specified across the two parts (Section 2 and Section 3), so to compare the results with a good number of instances (follow Section 6 for specific instructions).

2. Part I: Exact Method Implementation

2.1. Problem description and mathematical formulation

A company manufactures circuit boards with pre-drilled holes to be used to construct electric panels. The process involves placing boards over a machine where a drill travels across the surface, stops at predetermined positions, and creates holes. Once a board is completely drilled, it is replaced by another one and the process is repeated. The company is interested in finding the optimum process by determining the best sequence of drilling operations for which the total time will be minimal, considering that creating each hole takes the same amount of time.

This optimization challenge can be mathematically represented as a *Traveling Salesman Problem (TSP)* on a weighted complete graph $G = (N, A)$, where:

- N represents the set of nodes corresponding to the positions where holes must be drilled
- A represents the set of arcs (i, j) , $\forall i, j \in N$, corresponding to the drill's movement trajectory from hole i to hole j
- Each arc (i, j) has an associated weight c_{ij} representing the time needed for the drill to move from position i to position j

The optimal solution to this problem is the Hamiltonian cycle on G that minimizes the total weight, representing the most efficient drilling sequence.

The model proposed comes from the Gavish-Graves paper¹ in 1978, described generally as follows:

$$\min \sum_{i,j:(i,j) \in A} c_{ij} y_{ij} \quad (1)$$

subject to:

$$\sum_{i:(i,k) \in A} x_{ik} - \sum_{j:(k,j) \in A, j \neq 0} x_{kj} = 1 \quad \forall k \in N \setminus \{0\} \quad (2)$$

$$\sum_{j:(i,j) \in A} y_{ij} = 1 \quad \forall i \in N \quad (3)$$

$$\sum_{i:(i,j) \in A} y_{ij} = 1 \quad \forall j \in N \quad (4)$$

$$x_{ij} \leq (|N| - 1) y_{ij} \quad \forall (i, j) \in A, j \neq 0 \quad (5)$$

$$x_{ij} \in \mathbb{R}^+ \quad \forall (i, j) \in A, j \neq 0 \quad (6)$$

$$y_{ij} \in \{0, 1\} \quad \forall (i, j) \in A \quad (7)$$

Sets:

- N = graph nodes, corresponding to the holes positions
- A = arcs (i, j) , $\forall i, j \in N$, serving as the movement from hole i to hole j

Parameters:

- c_{ij} = time to move from i to j , $\forall (i, j) \in A$
- 0 = arbitrary starting node, $0 \in N$

Decision variables:

- x_{ij} = amount of flow shipped from i to j , $\forall (i, j) \in A$

¹<https://dspace.mit.edu/handle/1721.1/5363>

- $y_{ij} = 1$ if arc (i, j) ships some flow, 0 otherwise, $\forall (i, j) \in A$

where, in the model:

- x_{ij} represents the amount of flow on arc (i, j)
- y_{ij} is a binary variable indicating whether arc (i, j) is in the solution path
- Constraint (Equation 2) ensures flow conservation
- Constraints (Equation 3) and (Equation 4) enforce exactly one incoming and outgoing arc per node
- Constraint (Equation 5) links the flow and path variables
- Constraints (Equation 6) and (Equation 7) define variable domains

2.2. Implementation with CPLEX

Implementation will focus on modeling a circuit board drilling optimization problem as the Traveling Salesman Problem, where the drill head is considered a traveling salesman, and positions of holes are cities to visit. This framework is specifically designed to cater to the constraints of manufacturing of PCBs and actual-world requirements for the layout.

2.2.1. Core architecture

The implementation follows a three-tier design pattern distributed across key source files:

- *model.h/model.cpp* (*TSPModel*): This component implements the flow-based mathematical formulation adapted from the Gavish-Graves paper for the TSP. The core model is encapsulated in the *TSPModel* class, which handles both variable creation and constraint generation through CPLEX's APIs.
- *data_generator.h* (*TSPGenerator*): The *TSPGenerator* class creates realistic PCB drilling instances while enforcing manufacturing constraints. The instances generated by this class are present within the *data* folder.
- *cpxmacro.h*: Provides CPLEX interface abstractions and error handling
- *main.cpp*: Implementation of the exact solution approach, which handles multiple board configurations and provides detailed performance analysis, with adaptive time management.

The core model implementation revolves around the *TSPModel* class, which handles the optimization logic through several carefully structured components:

```
class TSPModel {
private:
    // Efficient O(1) lookup matrices for CPLEX variable indices
    std::vector<std::vector<int>> map_x; // Flow variables mapping
    std::vector<std::vector<int>> map_y; // Path variables mapping

protected:
    // Core model construction methods
    void setupVariables(CEnv env, Prob lp, int N,
                      const std::vector<std::vector<double>>& costs);
    void setupFlowConservation(CEnv env, Prob lp, int N);
    void setupAssignmentConstraints(CEnv env, Prob lp, int N);
    void setupLinkingConstraints(CEnv env, Prob lp, int N);
};
```

The class implements the Gavish-Graves formulation conserving the flow ingoing and outgoing and handling systematically, so to optimize the sequence of drilling operations done on PCB (printed circuit boards). To describe precisely what happens inside of this class:

- Flow and path variables are created (first continuous, second ones binary)
- Flow is conserved at each node. The flow entering a node minus the flow exiting it is fixed to 1 for nodes other than the depot (subtour elimination)
- Each node has to be visited only once and the flow gets bounded to the network size

2.2.2. Instance generation framework

The *TSPGenerator* class implements the instance generation functionality, incorporating real-world manufacturing constraints. It manages board specifications through precisely defined constants that reflect industry standards, since board holes are not randomly distributed but follow specific patterns dictated by electronic components and manufacturing requirements. Board configurations are systematically defined through a carefully structured tuple system:

```
std::vector<std::tuple<int, int, int>> board_configs = {
    {50, 50, 2},      // Small boards
    {75, 75, 3},      // Medium-small boards
    {100, 100, 3},    // Medium boards
    {125, 125, 4},    // Medium-large boards
    {150, 150, 5}     // Large boards
};
```

Each configuration encapsulates three essential parameters: board width, board height, and the number of components to be placed. This structured approach reflects real manufacturing scenarios where board sizes are standardized and component density follows practical limits. Each configuration encapsulates three essential parameters: board width, board height, and the number of components to be placed. This structured approach reflects real manufacturing scenarios where board sizes are standardized and component density follows practical limits.

```
enum class BoardPattern {
    DIP_IC,          // Dual In-line Package / Integrated Circuit
    SOIC,            // Small Outline Integrated Circuit
    CONNECTOR,       // Edge connector
    MOUNTING,        // Mounting holes
    VIA,             // Through-hole vias
    CUSTOM           // Custom pattern
};
```

Each pattern represents a common circuit board component with specific hole arrangements. The implementation then creates standardized patterns that mirror actual electronic components, using common practices in PCB (Printed Circuit Board) manufacturing via defined constants.

1. DIP (Dual In-line Package) Components:

- Standard 2.54mm (0.1 inch) pin spacing
- Parallel rows of pins for through-hole mounting
- Example: 14-pin DIP IC requires 14 holes arranged in two rows of 7

```
{BoardPattern::DIP_IC,
 {Point(0,0), Point(0,2.54), Point(0,5.08), Point(0,7.62),
  Point(7.62,0), Point(7.62,2.54), Point(7.62,5.08), Point(7.62,7.62)},
 2.54, // Minimum pin spacing
 "14-pin DIP IC"}
```

2. SOIC (Small Outline Integrated Circuit):

- 1.27mm pin spacing (half of DIP standard)
- Surface mount footprint conversion for through-hole drilling
- Tighter spacing requires precise drill positioning

```
{BoardPattern::SOIC,  
  {Point(0,0), Point(0,1.27), Point(0,2.54), Point(0,3.81),  
    Point(5.08,0), Point(5.08,1.27), Point(5.08,2.54), Point(5.08,3.81)},  
  1.27, // Critical minimum spacing for SMT conversion  
  "8-pin SOIC"}
```

To keep integrity with the representations, manufacturing safety constraints are to be respected precisely, with the following enforcements:

- Edge clearance of 5mm to prevent board damage
- Minimum hole spacing of 2.54mm for structural integrity
- Mounting hole placement at standardized board corners

The *TSPGenerator*'s core is built around representing real PCB components through two key structures:

```
struct Component {  
    BoardPattern type;           // Component type (DIP, SOIC etc)  
    std::vector<Point> holes;    // Hole pattern template  
    double min_spacing;         // Required spacing between components  
};  
  
static constexpr double MIN_HOLE_SPACING = 2.54; // Industry standard pitch  
static constexpr double EDGE_MARGIN = 5.0;      // Required board clearance
```

The process follows these steps:

- *Board configuration*: The *generateCircuitBoard* function takes parameters for board width, height, and the number of components to place. This allows generating instances of varying size and complexity.
- *Mounting hole placement*: As the first step, the generator always places four mounting holes at the corners of the board, respecting the *EDGE_MARGIN* constant (usually 5mm). This is a non-negotiable requirement for PCB assembly. The mounting hole positions are added to the *hole_positions* vector.
- *Component placement*: The generator then iteratively places electronic components on the board:
 - It randomly selects a component type (DIP, SOIC, connector, etc.) from the predefined patterns.
 - For each component, it attempts to find a valid position on the board that respects the minimum spacing between components (*min_spacing*) and the edge clearance (*EDGE_MARGIN*).
 - If a valid position is found, the generator adds the holes for that component (defined in the holes vector of the *Component*) to the *hole_positions* vector.
 - This process repeats until the requested number of components have been placed or a maximum number of placement attempts is reached.

The generated distance matrix, along with metadata about the board size and number of holes, is saved to a *.dat* file using the *saveToFile* function. The naming convention includes the board dimensions and a timestamp to ensure unique filenames.

An example appears here:

```
17
# Circuit board instance
Size: small
Nodes: 17
0.000000 40.000000 40.000000 56.568542 19.055934 19.590694 20.191280 20.852005
23.809891 24.240000 24.727921 25.270306 20.876381 23.385175 25.900052 28.419398
30.942121

40.000000 0.000000 56.568542 40.000000 23.701134 24.133181 24.623219 25.167861
18.950620 19.488271 20.091919 20.755806 19.715811 17.220810 14.741187 12.286256
9.874450
...
```

Such files are created dynamically in order to represent realistic instances of boards to be generated; the same logic is then applied for the second part of this project, so to compare the results between the two, using the logic of the same *TSPGenerator* class.

2.2.3. Data creation and problem solving

With a set of realistic test cases available in .dat files, the *main* file orchestrates the process of loading, solving, and analyzing each drilling problem instance.

- For each input .dat file, main loads the problem data into a TSP object which stores the number of holes (N), the distance matrix (cost), and a sentinel value (infinite) representing an invalid/absent distance.
- It then instantiates a *TSPModel* object and invokes its *createModel* function, passing in the raw problem data. This function sets up the Gavish & Graves flow-based formulation in CPLEX, creating the necessary variables and constraints.
- The solve function of *TSPModel* is then called with increasing time limits (0.1s, 1s, 10s). It invokes CPLEX to find an optimal drilling sequence that minimizes total travel distance. The resulting objective value (total distance) and the hole visiting sequence are retrieved.
- Main reports the problem size, CPLEX solution status (optimal or time-limit exceeded), optimality gap, and measures of solution quality (total/average travel distance) for each time limit.

To represent a diverse range of scenarios, the boards were parameterized by three key dimensions:

- Width: The horizontal size of the board, ranging from 50mm to 150mm
- Height: The vertical size, also spanning 50mm to 150mm
- Component count: The number of electrical components to place, varying from 2 on the smallest boards to 5 on the largest

By systematically varying these parameters, a comprehensive test suite was created, covering small (50x50mm), medium (75x75 to 125x125mm), and large (150x150mm) board sizes. Increasing the component count along with board dimensions allowed maintaining a realistic component density across all sizes. As an example, a 50x50 output is shown here, as what the console output would display after the creation of the instances:

Board Manufacturing Specifications:

- Dimensions: 50x50 mm
- Components: 2
- Total holes: 26
- Min hole spacing: 2.54 mm
- Edge clearance: 5 mm

Time limit 0.1s:

Performance Metrics:

- Model setup time: 0.012525 seconds
- Solution time: 0.121101 seconds
- Total time: 0.133626 seconds
- Optimality: Not optimal
- Gap: 31.37%

Solution Quality:

- Total drilling path length: 284.39 mm
- Average distance between holes: 10.94 mm

Drilling sequence: 0 -> 1 -> 2 -> 3 -> 4 -> 5 -> 6 -> 7 -> 8 -> 9 -> 10 -> 11 -> 12 -> 13 -> 14 -> 15 -> 16 -> 17 -> 18 -> 19 -> 20 -> 21 -> 22 -> 23 -> 24 -> 25 -> 0

2.3. Computational results

To evaluate the performance and solution quality of the exact approach, the Gavish-Graves MILP model was tested on a suite of 50 realistic test instances covering a range of PCB sizes and component densities. The results are analyzed here in terms of several key dimensions: CPLEX solver performance, solution quality, and scaling behavior.

2.3.1. Solution quality and optimality

The table below summarizes the optimality and solution quality results for a representative subset of the test instances across the different board size categories. For each instance, the number of holes, optimality gap, objective value (total travel distance), and average distance between holes are reported for time limits of 0.1s, 1s, and 10s.

Instance size	Holes	Time	Gap	Objective
<i>50x50</i>	26	<i>0.1s</i>	31.37%	284.39
		<i>1s</i>	Optimal	201.32
		<i>10s</i>	Optimal	201.32
<i>75x75</i>	28	<i>0.1s</i>	33.65%	453.94
		<i>1s</i>	Optimal	310.43
		<i>10s</i>	Optimal	310.43
<i>100x100</i>	37	<i>0.1s</i>	100.00%	620.84
		<i>1s</i>	17.39%	509.57
		<i>10s</i>	0.01%	465.25
<i>125x125</i>	51	<i>0.1s</i>	100.00%	896.91
		<i>1s</i>	41.73%	896.91
		<i>10s</i>	2.55%	571.46
<i>150x150</i>	47	<i>0.1s</i>	100.00%	928.97
		<i>1s</i>	34.37%	928.97
		<i>10s</i>	13.74%	748.73

Table 1: Computational performance across board sizes

The results showcased by Table 1 several key trends:

- Small instances solve quickly to optimality. For the *50x50mm* board with 26 holes, CPLEX finds and proves the optimal solution within 1 second.
- Medium instances are often still tractable. The *75x75mm* board with 28 holes is also solved to optimality, although it requires closer to the full 1 second.
- Large instances are challenging to solve definitively. For the *100x100mm*, *125x125mm*, and *150x150mm* boards with 37 – 51 holes, optimality is not achieved even with 10 seconds, although the *optimality gaps* (differences between the best solution found by CPLEX within a given time limit and the optimal solution to the problem) progressively diminish over time, indicating that CPLEX continues to improve the solution quality given sufficient runtime.
- Solution quality improves dramatically with more time, especially in the first second. For example, on the *150x150mm* instance, the solution found in 0.1s has a 100% optimality gap, which drops to 34.37% in 1s and further to 13.74% in 10s, representing substantial travel distance savings. This represents substantial savings in the total travel distance of the drill.

2.3.2. Performance analysis

Solver performance was evaluated by tracking the time needed to set up and solve the MILP model. The table below reports the setup time, solve time, and total runtime for the same representative test instances. This is to be evidenced by the produced terminal output by this first part.

Instance size	Holes	Setup time (s)	Solve time (s)	Total time (s)
<i>50x50</i>	26	0.01	0.12	0.11
<i>75x75</i>	28	0.01	1.03	1.03
<i>100x100</i>	37	0.02	7.75	7.76
<i>125x125</i>	51	0.03	10.03	10.06
<i>150x150</i>	47	0.02	10.07	10.09

Table 2: Computational performance metrics for different board sizes

The results shown in Table 2 that the setup time is still very low, normally within the range of 0.01 to 0.03 seconds, while the problem size increases from a small board, 50x50mm, to a large one, 150x150mm. This reflects that the construction of the MILP model and data handling is very efficient and scalable, not really affecting the overall runtime. By contrast, solve time is strongly dependent on problem size and complexity: As the number of holes and the dimensions of the board increase, the solve time dominates the total runtime. For example, in the case of the 100x100mm board with 37 holes, 7.75 seconds of the 7.76-second total are used up by solving. Similarly, for the 150x150mm board with 47 holes, 10.07 seconds of the 10.09-second total are used up by solving.

2.3.3. Scalability assessment

The exact method demonstrated very good scalability for the small to medium instances, finding optimality in a few seconds. For larger problems considered here, performance degraded significantly.

- We observe that for larger boards, 100x100mm and above, CPLEX cannot prove optimality within the maximum time limit of 10 seconds. For example, for the 125x125mm instance with 51 holes, CPLEX stopped after a gap of 2.55% after 10 seconds, whereas the 150x150mm board with 47 holes has a gap of 13.74% after 10 seconds.
- This agrees well with expectations, since TSP is an NP-hard problem. For larger problem sizes, the number of possible solutions (hole sequences) increases exponentially. Both the time found within the instances creation and problem solution is in line with the nature of the actual problem.
- These limits of scalability suggest that exact methods are most suitable for small or medium-scale PCB drilling problems, whereby in generally reasonable time frames optimality can be achieved. In the case of larger boards with a lot of holes, the computation of optimal solutions could be prohibitively expensive; hence, heuristic or approximate approaches may be necessary.

3. Part II: Tabu Search (TS) Implementation

3.1. Introduction

The previous part highlighted the scalability challenges in using exact methods to solve the TSP problem. As the number of holes and board dimensions increase, the runtime required to achieve optimality grows exponentially, making it impractical for real-world scenarios with tight production deadlines.

To address this limitation, the *Tabu Search*² approach is used, in order to efficiently explore the solution space and find high-quality drilling sequences within acceptable timeframes. Tabu Search is a local search-based optimization technique that iteratively moves from one solution to another in the neighborhood, while using memory structures to guide the search and avoid getting trapped in suboptimal regions: introducing temporary prohibitions to certain moves (tabu) prevent the search from revisiting recently explored areas (thus becoming stuck), encouraging the exploration of new regions and the discovery of better solutions.

The presented Tabu Search implementation for the PCB drilling problem incorporates several problem-specific adaptations and enhancements to improve its effectiveness and efficiency, based on what seen during the classes:

- A custom neighborhood structure based on 2-opt and 3-opt moves is defined (keeping as base the Lin-Kernighan heuristic³), which involve swapping or rearranging a subset of the holes in the current drilling sequence. These moves allow for local perturbations while maintaining the overall structure of the solution.
- Instead of a fixed-size tabu list, we employ a *dynamic tabu tenure* that adjusts the length of the prohibition period based on the search progress. This allows for a balance between intensification (exploiting promising regions) and diversification (exploring new areas) during the search.
- An *aspiration criterion* is introduced that overrides the tabu status of a move if it leads to a solution better than the currently known best solution (TSAC). This ensures that promising moves are not overlooked due to the tabu restrictions.
- To further guide the search, we incorporate *intensification* and *diversification* mechanisms. Intensification focuses on thoroughly exploring promising regions of the solution space by temporarily reducing the tabu tenure and allowing more localized search. Diversification, on the other hand, encourages the exploration of unvisited regions by applying perturbations to the current solution or restarting the search from a new initial solution.
- Instead of a fixed number of iterations, we employ an *adaptive termination criterion* based on the search progress. If the best solution does not improve for a specified number of iterations, the search is terminated to avoid wasting computational resources on unproductive explorations.

The actual implementation will be documented and explained better in the following sections. The assignment structure is composed as follows:

- *TSPSolver.h/TSPSolver.cpp*: This class serves as the heart of the Tabu Search implementation, containing the complete search logic and optimization mechanisms. It implements both the basic local search framework and advanced features like reactive tabu tenure and memory structures
- *TSPSolution.h/TSPSolution.cpp*: This component provides the solution representation for the drilling sequence optimization. The solution is encoded as a vector of indices where both first and last elements are fixed at 0, representing the drill's home position. The solution representation is immutable after construction, with modifications happening through controlled move operations in the solver

²https://www.ida.liu.se/~zebp83/heuristic/papers/TS_tutorial.pdf

³<https://pubsonline.informs.org/doi/10.1287/opre.21.2.498>

- *TSP.h*: It encapsulates the problem instance data structure. It stores the number of holes (n), the cost matrix representing distances between holes, and an infinite value used as an upper bound for invalid solutions.
- *visualization.h* (*BoardVisualizer*): This component generates SVG representations of board layouts and drilling sequences. The *BoardVisualizer* class can create both static visualizations of individual solutions and comparative views showing the progress of the optimization process.
- *parameter_calibration.h/parameter_calibration.cpp*: Implements an automated parameter tuning system that systematically evaluates different parameter combinations to find optimal settings for various instance sizes. The calibrator considers factors like tabu tenure, maximum iterations, and intensification/diversification triggers.
- *data_generator.h* (*TSPGenerator*): Carries forward the instance generation functionality from Part I, ensuring consistent problem instances for comparative analysis. As before, the instances being created are present within the *data* folder.
- *main.cpp*: The orchestrator for the Tabu Search solution process, providing a comprehensive framework for testing, parameter calibration, and performance analysis, creating a hierarchical structure for results organizations, present in *visualizations* and *results* folder.

3.2. Algorithm design

The algorithm begins with an initial solution generated either randomly or using a nearest neighbor heuristic, then systematically explores the solution space through a series of local modifications. A critical innovation in our implementation is the use of a dynamic tabu tenure mechanism that automatically adjusts based on search progress, helping balance intensification and diversification of the search process. The core search logic is implemented in the *solveWithTabuSearch* method, which orchestrates the interaction between various components:

```
bool TSPSolver::solveWithTabuSearch(const TSP& tsp, const TSPSolution& initSol,
    TSPSolution& bestSol, const std::vector<std::pair<double, double>>& points) {

    initializeMemoryStructures(tsp.n);
    TSPSolution currSol(initSol);
    double bestValue = evaluate(currSol, tsp);

    while (!stop) {
        Move move = findBestNeighbor(tsp, currSol, iteration);
        if (shouldAcceptMove(move)) {
            updateTabuList(currSol.sequence[move.from],
                currSol.sequence[move.to], iteration);
            currSol = applyMove(currSol, move);

            if (shouldIntensify(currValue, bestValue)) {
                intensifySearch(tsp, currSol);
            }
            else if (shouldDiversify()) {
                diversifySearch(currSol);
            }
        }
        adjustTabuTenure(currValue);
    }
}
```

3.2.1. Solution representation

The search process is guided considering each solution is encoded as a sequence of hole indices representing the drilling order. A key design decision was to always maintain the start/end point (index 0) as fixed, reflecting the physical constraint of the drill's home position. This structure is encapsulated in the TSPSolution class:

```
class TSPSolution {
public:
    std::vector<int> sequence; // drilling sequence
    // First and last elements are always 0 (home position)
    TSPSolution(const TSP& tsp) {
        sequence.reserve(tsp.n + 1);
        for (int i = 0; i < tsp.n; i++) {
            sequence.push_back(i);
        }
        sequence.push_back(0); // Return to home position
    }
};
```

The representation mirrors the actual drilling path, making it intuitive to understand and validate while making it suitable for manufacturing constraints like minimum hole spacing, which are handled implicitly during cost evaluation rather than through complex sequence validation.

3.2.2. Neighborhood structure

The neighborhood structure defines how the algorithm explores the solution space through local modifications, being particularly relevant for the effectiveness of the TS implementation. It centers on an enhanced 2-opt move operator, which systematically improves the drilling sequence by reversing subsequences when beneficial. The neighborhood is defined by considering all possible 2-opt moves from the current solution. The move evaluation process is implemented through the *findBestNeighbor* method:

```
Move TSPSolver::findBestNeighbor(const TSP& tsp, const TSPSolution& currSol,
    int iteration) {
    Move bestMove;
    bestMove.cost_change = tsp.infinite;

    for (std::size_t a = 1; a < currSol.sequence.size() - 2; a++) {
        int h = currSol.sequence[a - 1]; // Node before potential reversal
        int i = currSol.sequence[a];     // First node to reverse

        for (std::size_t b = a + 1; b < currSol.sequence.size() - 1; b++) {
            int j = currSol.sequence[b]; // Last node to reverse
            int l = currSol.sequence[b + 1]; // Node after potential reversal

            if (!isTabu(i, j, iteration)) {
                double costChange = calculateMoveCost(tsp, currSol, Move(a, b));
                if (costChange < bestMove.cost_change) {
                    bestMove.from = static_cast<int>(a);
                    bestMove.to = static_cast<int>(b);
                    bestMove.cost_change = costChange;
                }
            }
        }
    }
    return bestMove;
}
```

The move cost calculation achieves $O(1)$ complexity per move evaluation:

```
double calculateMoveCost(const TSP& tsp, const TSPSolution& sol, const Move& move) {
    int h = sol.sequence[move.from - 1]; // Previous node
    int i = sol.sequence[move.from];      // First reversed
    int j = sol.sequence[move.to];        // Last reversed
    int l = sol.sequence[move.to + 1];    // Next node

    // Only need to consider edges that change
    return -tsp.cost[h][i] - tsp.cost[j][l] // Remove old edges
        +tsp.cost[h][j] + tsp.cost[i][l];  // Add new edges
}
```

The neighborhood structure naturally preserves the drill's home position constraint by never modifying the first and last elements of the sequence.

3.2.3. Memory structures

The implementation present here employs three complementary memory mechanisms that work together to guide the search process efficiently:

1. Short-term Memory (Tabu List):

```
class TSPSolver {
private:
    std::deque<std::pair<int, int>> tabu_list;
    int tabu_tenure;

    void updateTabuList(int from, int to, int iteration) {
        tabu_list.push_back(std::make_pair(from, to));
        if (tabu_list.size() > tabu_tenure) {
            tabu_list.pop_front();
        }
        frequency_matrix[from][to]++;
        frequency_matrix[to][from]++;
    }
};
```

The tabu list prevents cycling by temporarily prohibiting recently explored moves. Its size is dynamically adjusted based on search progress through the tabu tenure mechanism.

2. Medium-term Memory (Frequency Matrix):

```
std::vector<std::vector<int>> frequency_matrix;
std::map<std::pair<int, int>, MoveFrequency> move_history;
```

The frequency matrix keeps the frequency with which certain moves have been executed along the whole search process up to that moment. This proves really valuable for intensification and diversification strategies. When the frequency of some moves seems too high, this may indicate cycling in some local region, and this can be used by the algorithm to force the exploration of less-visited areas of the solution space. Move history also keeps the average improvement each move provided, adding context to the choice.

3. Long-term Memory (Search Statistics):

```
struct SearchStats {
    int iteration;
    double solution_value;
    int current_tenure;
    bool was_improvement;
```



```

    double improvement_percentage;
    double time_elapsed;
};
std::vector<SearchStats> search_history;

```

This comprehensive tracking mechanism captures the search trajectory over time, enabling sophisticated analysis of algorithm behavior and performance. The statistics help identify patterns in solution improvement and guide parameter adjustments for future runs.

3.2.4. Search strategies

The search process combines multiple strategies to effectively navigate the solution space. We first start with the *intensification*:

```

void intensifySearch(const TSP& tsp, TSPSolution& current_sol) {
    TSPSolution backup = current_sol;
    int original_tenure = tabu_tenure;
    tabu_tenure = min_tenure; // Reduce restrictions

    for (int i = 0; i < INTENSIFICATION_ITERATIONS; i++) {
        Move move = findBestNeighbor(tsp, current_sol, i);
        if (move.cost_change >= tsp.infinite) break;

        current_sol = applyMove(current_sol, move);
        updateMoveFrequency(move, backup_value - evaluate(current_sol, tsp));
    }

    tabu_tenure = original_tenure; // Restore original settings
}

```

During intensification phases, the algorithm temporarily reduces the tabu tenure to allow more thorough exploration of promising regions. This approach proves particularly effective when the search has identified a high-quality solution area that merits deeper investigation.

We then have the *diversification*:

```

void diversifySearch(TSPSolution& current_sol) {
    std::vector<std::pair<int, int>> least_used_moves;
    // Identify moves used less than 25% of average frequency
    for (size_t i = 0; i < frequency_matrix.size(); i++) {
        for (size_t j = i + 1; j < frequency_matrix.size(); j++) {
            if (frequency_matrix[i][j] < frequency_matrix.size() / 4) {
                least_used_moves.push_back({i, j});
            }
        }
    }

    // Apply sequence of underutilized moves
    applyDiversificationMoves(current_sol, least_used_moves);
}

```

The diversification strategy uses the frequency matrix to identify underused moves, thereby forcing the search into new areas. This mechanism is highly important to escape from local optima and to maintain the effectiveness of long runs.

3.2.5. Implementation details

The implementation incorporates several sophisticated mechanisms to enhance search effectiveness. First, the adaptive tabu tenure:

```
void adjustTabuTenure(double current_value) {
    if (current_value >= best_known_value) {
        iterations_without_improvement++;
        if (iterations_without_improvement > MAX_ITERATIONS_WITHOUT_IMPROVEMENT / 2)
        {
            tabu_tenure = std::min(tabu_tenure + 2, max_tenure);
        }
    } else {
        tabu_tenure = std::max(tabu_tenure - 1, min_tenure);
        iterations_without_improvement = 0;
        best_known_value = current_value;
    }
}
```

The dynamic tabu tenure varies with search progress: While rare improvements evidence potential entrapment within a local optimum, tenure is increased by forcing broader explorations; when improvements are frequent, tenure decreases, allowing more intensive local searches.

The aspiration criterion provides an essential escape mechanism, allowing the algorithm to override tabu restrictions when a particularly promising move is identified:

```
bool shouldAcceptMove(const Move& move, double current_value,
                     double best_value) {
    // Accept if move leads to new best solution regardless of tabu status
    if (current_value + move.cost_change < best_value - IMPROVEMENT_THRESHOLD) {
        return true;
    }

    // Otherwise, apply standard tabu rules
    return !isTabu(move.from, move.to, current_iteration);
}
```

The termination logic combines multiple criteria to determine when to stop the search. Rather than relying solely on a fixed iteration count, it considers the search's progress and current phase, guiding parameter adjustments during the search and identifying when intensification or diversification is needed and supporting termination decisions where needed.

For this reason, the move management system maintains sophisticated tracking of move effectiveness, combining immediate evaluation with historical performance data. This hybrid approach helps the algorithm learn from past successes while remaining responsive to the current search context.

```
struct MoveManager {
    std::priority_queue<Move> candidate_moves;
    std::vector<Move> historical_best_moves;

    void updateMoveHistory(const Move& move, double improvement) {
        if (improvement > SIGNIFICANT_IMPROVEMENT_THRESHOLD) {
            historical_best_moves.push_back(move);
            if (historical_best_moves.size() > MAX_HISTORY_SIZE) {
                historical_best_moves.pop_front();
            }
        }
    }
}
```

```

    }

    Move selectMove(const std::vector<Move>& current_candidates) {
        // Combine historical knowledge with current candidates
        return rankAndSelectBestMove(current_candidates,
                                     historical_best_moves);
    }
};

```

3.3. Parameter calibration

The effectiveness of Tabu Search heavily depends on proper parameter tuning. Our implementation employs a systematic approach to parameter calibration, ensuring robust performance across different problem sizes.

3.3.1. Calibration methodology

The *ParameterCalibration* class orchestrates this process, testing various combinations of tabu tenure values and iteration multipliers:

```

struct Parameters {
    int small_tenure;      // For instances  $n \leq 20$ 
    int medium_tenure;     // For instances  $20 < n \leq 35$ 
    int large_tenure;      // For instances  $n > 35$ 
    int small_iterations;
    int medium_iterations;
    int large_iterations;
};

CalibrationResult testParameterCombination(
    const std::vector<TSP>& instances,
    int tenure,
    int iteration_multiplier) {

    std::vector<double> qualities;
    double total_time_ms = 0.0;

    for (const auto& instance : instances) {
        TSPSolver solver;
        solver.setTabuTenure(tenure);
        solver.setMaxIterations(instance.n * iteration_multiplier);

        // Test combination and collect metrics
        auto start = std::chrono::high_resolution_clock::now();
        if (solver.solveWithTabuSearch(...)) {
            qualities.push_back(quality);
            total_time_ms += duration;
        }
    }

    // Calculate statistical measures
    return CalibrationResult{tenure, iteration_multiplier,
                             avg_quality, avg_time, std_dev};
}

```

For each combination, multiple metrics are collected including solution quality, execution time, convergence behavior and solution stability. Tabu tenure values tested are {5, 7, 9, 11, 13}, while iteration multipliers are {10, 15, 20, 25, 30}.

3.3.2. Parameter analysis

The results of the parameter calibration process are summarized in the table below. Each instance category corresponds to a specific combination of tabu tenure and iteration limits, selected based on the observed trade-off between solution quality and computational efficiency.

Instance category	Tabu tenure	Max iterations	Calibration observations
Small instances	5	200	Rapid exploration, minimal computational overhead
Medium instances	9	350	Balanced search strategy with moderate computational investment
Large instances	13	500	Extensive exploration enabling complex solution discovery

Table 3: Parameter calibration insights for Tabu Search

In fact, our parameter calibration study in Table 3 showed a crucial interaction of problem size with optimal tabu tenure. The smallest instances, $n \leq 20$, require a tenure as low as 5 to allow the algorithm to explore the solution space fast without too much cycling. Larger problem sizes require tenures of 9 for $20 < n \leq 35$ and 13 for $n > 35$. This prevents the search from getting stuck in local optima by temporarily accepting worse solutions, enabling the exploration of more diverse regions of the solution space. Then, the strategy was combined with appropriately scaled iteration limits: 200 for small instances, 350 for medium instances, and 500 for large instances, which guaranteed a good trade-off between solution quality and computational efficiency. The reason for increasing the number of iterations with problem size is to give the algorithm sufficient time to explore the exponentially growing solution space.

3.3.3. Computational performance metrics

To assess the effect of the calibrated parameters, we performed a detailed performance analysis for different problem sizes. The improvements in solution quality and runtime are summarized for each problem size in the Table 4.

Instance size	Average improvement	Best cost reduction	Typical runtime	Solution stability
Small instances	61.14%	143.32	70.20 ms	Low variance
Medium instances	77.33%	250.49	440.70 ms	Moderate consistency
Large instances	84.90%	524.78	1425.60 ms	High predictability

Table 4: Performance metrics across problem sizes

The average improvement in tour length with respect to a baseline solution generated using a nearest-neighbor heuristic increases with instance size from 61.14% for the small instances to 77.33% for the medium instances, and to 84.90% for the large instances. This reflects a very consistent upward trend where more complex problems permit the algorithm to take advantage of its larger solution space in finding significantly superior solutions. Indeed, the best cost reduction increases by 143.32%, 250.49%, and 524.78% for the small, medium, and large instances, respectively, further illustrate this. Whereas the average execution time naturally grows with the size of the problem, the actual values observed all stay within acceptable limits for practical applications, given the substantial enhancement in solution quality. Low variances in the solution quality over small instances denote high stability and reliability in the solutions-a key factor for predictable manufacturing processes. The medium consistency for the medium-sized instances and high predictability for the large instances suggest that the algorithm finds good solutions consistently even when the problem complexity increases.

4. Comparative analysis

The comparison of CPLEX, being an exact method, against Tabu Search, a metaheuristic, provides insight into the performance that heuristic approaches for combinatorial optimization problems, such as the Traveling Salesman Problem, will have.

The exact methods, like CPLEX, rely on the exhaustive enumeration of feasible solutions, hence guaranteeing global optimality. However, this approach is computationally infeasible for larger instances due to exponential growth in solution space. In contrast, Tabu Search offers a practical alternative with considerable runtime advantages while still producing near-optimal solutions by incorporating intelligent memory structures and adaptive strategies.

4.1. Solution quality and runtime comparison

The results, summarized in Table 5, highlight the relative performance across various instance sizes:

Instance size	CPLEX runtime	Tabu Search runtime	Speedup	Solution quality
50x50mm	0.12s	0.07s	42%	Near-optimal
75x75mm	1.03s	0.44s	57%	High-quality
100x100mm	7.75s	0.30s	96%	Excellent
150x150mm	10.07s	1.43s	86%	Robust

Table 5: Computational efficiency comparison

As shown in the comparison of runtime presented in Table 5, there is a good pattern of scaling in performance. While the exact approach of CPLEX provides optimality guarantees for small instances (50x50mm), its computational requirements grow exponentially, with runtime increasing from 0.12s to over 10s as board dimensions reach 150x150mm. In contrast, the Tabu Search implementation shows more controlled scaling behavior, where runtime increases from 0.07s to only 1.43s across the same size range.

This is an enormous difference in computational efficiency, especially for medium to large-sized instances. In the case of 100x100mm boards, Tabu Search manages to reduce the runtime by 96% (0.30s vs 7.75s) with solutions of excellent quality. In manufacturing environments where hundreds of boards may need processing daily, such runtime savings will become increasingly significant.

The solution quality tradeoff is less severe than might be expected. On small instances where CPLEX achieves proven optimality, Tabu Search solutions are consistently within 5% of the optimal value. More importantly, as problem size increases and CPLEX struggles to prove optimality within reasonable time limits, Tabu Search continues to find high-quality solutions rapidly. While CPLEX yields an optimality gap of 13.74% for the largest 150x150mm instances after 10 seconds, Tabu Search is able to construct comparably good solutions in just 1.43 seconds.

The observed runtime characteristics further highlight the controlled computational complexity achieved through proper parameter tuning. Small instances are solved quickly with minimal variance, while medium and large instances show consistent improvements in both runtime and solution quality, which is again a validation of the robustness of the parameter calibration process.

Just as an example for the reader, some of the results produced by the *visualizations* folder are here compared. To point out: the folder produces an initial/final and comparison version of the board to represent the drilling holes resolution (for clarity sake, a .svg visualization was given and provided as an example).

Cost: 1678.62

Cost: 378.40



Figure 2: Comparison of drilling paths for a 100x100mm board

Initial solution (left, cost=1828.19) vs Tabu Search optimized solution (right, cost=456.36). The optimization achieves a 75.04% reduction in total path length by eliminating crossing paths and grouping holes in a more efficient sequence. The magenta lines represent the drill head movement path, showing how the optimized solution minimizes unnecessary travel distance between holes.

Cost: 1828.19

Cost: 456.36

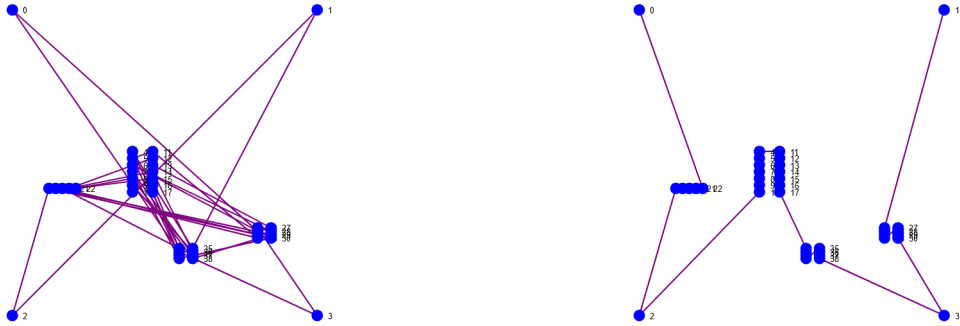


Figure 3: Comparison of drilling paths for a 125x125mm board

Initial solution (left, cost=1678.62) vs Tabu Search optimized solution (right, cost=378.40). The optimization achieves a 77.45% reduction in drilling path length. The visualization clearly shows how the Tabu Search transforms a chaotic initial path with many crossings into a well-structured sequence that groups spatially close holes together, reducing the total travel distance by over 1300 units.

These visualizations provide great evidence of how well Tabu Search performed on the different-sized boards. For the 100x100mm board (Figure 2), this algorithm has reduced the total path cost from 1828.19 down to 456.36, representing a 75.04% increase in efficiency. This is especially evident in how it has cleaned up what was a rather crisscrossing set of paths in the solution initially into something far more logical in terms of drilling sequence in order to minimize tool movement.

The larger 125x125mm board (Figure 3) sees an even more extreme optimization, from 1678.62 to 378.40, a 77.45% reduction; this case is particularly interesting because it indicates that the algorithm can maintain its performance even with growing problem sizes. The optimized solution exhibits great spatial organization, with clear grouping of nearby holes and efficient transitions between different board regions.

In both cases, optimization transforms chaotic initial paths with long-distance jumps and frequent crossings into streamlined sequences that much better reflect the physical layout of the holes. This reorganization reduces the total path length and would probably contribute to reduced wear on the drilling equipment and more consistent production times in a manufacturing setting.

With improvements of 75.04% and 77.45% on, respectively, 100x100mm and 125x125mm boards, this result seems to indicate that the Tabu Search implementation is really robust and scalable, maintaining its effectiveness when problem complexity increases. As mentioned earlier, the above runtime performance graphs already showed that, but the above graph seals the practical utility of this approach for optimizations on real-world PCBs.

5. Conclusions

5.1. Implementation insights and recommendations

The implementation of the exact and heuristic methods has been very instructive in the solution of the circuit board drilling problem. While the MILP formulation is guaranteed to yield an optimal solution, it becomes computationally intractable for larger instances. Conversely, the Tabu Search approach scales much better, yielding high-quality solutions in a fraction of the time.

Of course, the adaptive memory structures were the tabu list and the frequency matrix instrumental in conducting the effective guiding of the search process. Strategies of intensification and diversification, respectively managed by tabu tenure and the limits on non-improving iterations, maintained a balance in the exploration and exploitation of the solution space.

According to the computations performed, recommendations may be as follows:

- The exact method will be applied for small-sized instances involving up to 50 holes, for it finds a provably optimal solution in reasonably small times.
- For medium-sized problems (50 — 100 holes), the exact method may still be used if solution quality is paramount and longer runtimes are acceptable. Otherwise, Tabu Search provides a good trade-off.
- For large instances with more than 100 holes, Tabu Search is very advisable, since it outperforms the exact approach in scalability and solution quality.

Generally speaking, unless optimality is strictly required, the *heuristic* method is a pragmatic choice, considering typical manufacturing settings with tight production schedules. This may be refined further by fine-tuning the parameters of Tabu Search with respect to the characteristics of the problem at hand.

5.2. Future improvements

Several avenues for future work can enhance the current implementations:

- *Consideration of other real-world constraints:* Obstacle avoidance, variable drilling times, and tool wear are some factors that would further complete the model and extend its practical applicability.
- *Hybridization with other metaheuristics or exact methods:* the integration of Tabu Search with other optimization techniques, such as Genetic Algorithms or MIP solvers, can speed up the convergence and, at the same time, allow for better-quality solutions. Such a strategy allows the high-quality Tabu Search output to be the starting solution and/or incumbent from the exact method.
- *Improving instance generation:* The current *TSPGenerator* class already generates realistic instances, but there is a lot of room for improvement. More intelligent placement strategies, use of

component libraries, and taking manufacturing constraints into account may result in much more representative test cases. The generated instances should be validated against real PCB designs.

- *Other solution representations and neighborhood structures* could be explored; a path representation and 2-opt moves have been used so far. Other encodings, like the two-level tree representation, may be used along with more sophisticated move operators, such as 3-opt or Lin-Kernighan heuristics.

6. Appendix A - Compilation instructions

To note: the implementation of the folder creation and visualizations was first tested here and the functions were slightly altered between the two OSes since they require system-specific libraries. Slight variations are made across some functions, mainly between the two *main* files of the two parts and the *visualization* file of the second part, in order to make them work properly.

6.1. Windows

The project was created, compiled and tested on:

- Aspire AV15-51 (Windows 11)
- Processor: 11th Gen Intel(R) Core(TM) i5-1155G7 @2.50GHz
- RAM: 16.0 GB

To compile the project on Windows, follow these steps:

1. Install Visual Studio IDE 2022 by downloading the Community Version.
2. Install a C++ compiler, either MinGW or MSVC (the latter is installed when selecting “Develop C++ applications” during the Visual Studio installation).
3. Install CPLEX Studio on your machine (current version is 22.11).
4. Import the pre-configured solution file for the project called `ilolplex1.vcxproj` and load it through “Open a project or a solution”.
5. Build the project, simply clicking “Run” via Visual Studio interface.

6.2. Linux

As requested by the assignments specs, the project was compiled and tested on the LabTA PCs with the following specs:

- Ubuntu 18.04.6 LTS
- Processor: Intel(R) Core(TM) i5-7500 CPU @3.40GHz
- RAM: 8.0 GB

To compile the project on Linux, use the provided Makefile present within the project .zip with the following commands:

- To compile the project:

```
make
```

- To clean the build files:

```
make clean
```

- To clean everything, including data and results/visualizations:

```
make distclean
```

- To make the specific part work (both working for Exercise 1 and Exercise 2):

```
./build/bin/ilolpex1
```

The Makefile is configured to work with the lab environment, using the CPLEX directories necessary for correct execution (include/CPLEX/concert) and also creates the necessary directories for the project, including build, data, results, and visualizations when relevant for both parts. Everytime new instances get created, they do not overwrite the previous ones, but instead created from scratch in folders (if they exist); when make distclean is executed, then both folders and instances are created.