Chapter 3: Research Methodology

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CHAPTER 3

RESEARCH METHODOLOGY

3.1 Research Framework

This research adopts the *Design Science Research* (DSR) *methodology* developed by Hevner et al. (2004) and Peffers et al. (2007). DSR was chosen because the research focus is on developing technology artifacts (scheduling systems) that provide practical solutions for real problems in the hospitality industry.

3.1.1 Design Science Research Framework

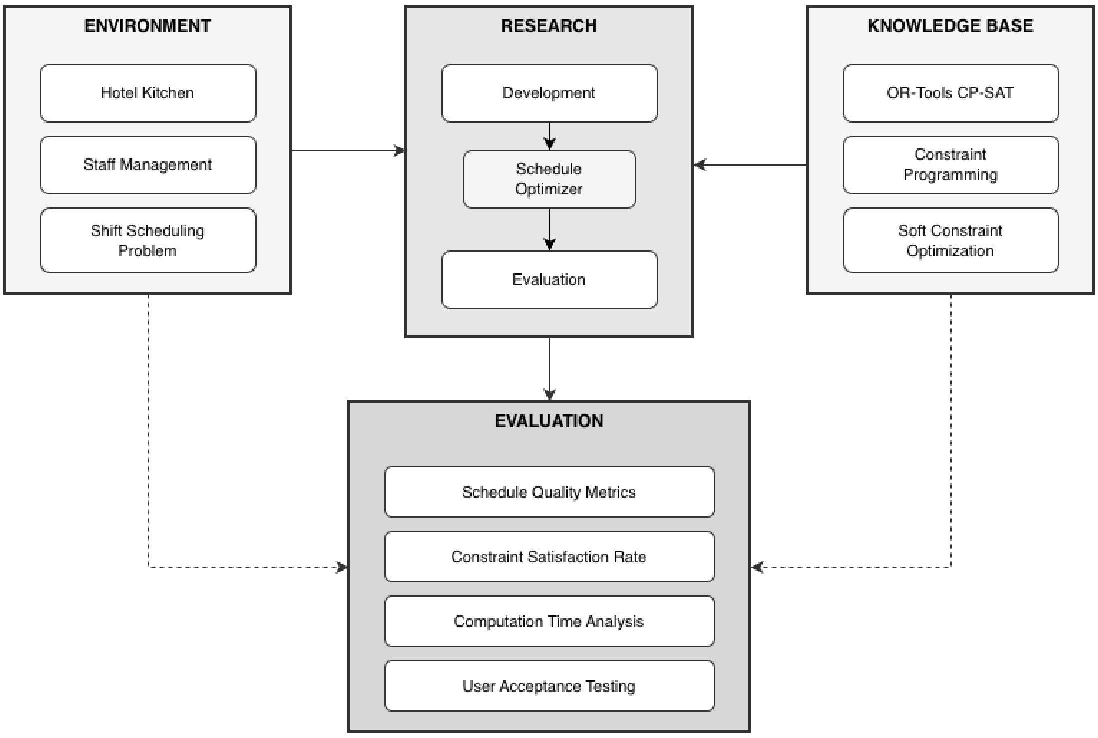


Figure 3.1: Design Science Research Framework (Adapted from Hevner et al., 2004)

Figure 3.1: Design Science Research Framework (Adapted from Hevner et al., 2004)

3.1.2 DSR Research Stages

Table 3.1: DSR Research Stages

Stage	Activity	Output
1. Problem Identification	Analysis of shift scheduling problems in hotel kitchen division	Problem statement & requirements
2. Define Objectives	Defining optimal solution criteria	Success metrics & KPIs
3. Design & Development	Development of CP-SAT model with soft constraints	Working prototype
4. Demonstration	Implementation on real case study	Deployed system
5. Evaluation	Testing and performance analysis	Evaluation report
6. Communication	Documentation and publication of results	Thesis & publications

3.2 Constraint Satisfaction Problem (CSP) Modeling

3.2.1 Formal Definition of CSP

According to Russell & Norvig (2020), *Constraint Satisfaction Problem* (CSP) is defined as a tuple (X, D, C) where:

- X = {x1, x2, ..., xn} is the set of variables
- D = {D1, D2, ..., Dn} is the domain for each variable
- C = {C1, C2, ..., Cm} is the set of constraints

3.2.2 CSP Formulation for Shift Scheduling

In the context of hotel kitchen division shift scheduling, CSP is formulated as follows:

Decision Variables:

X = {shifts[s,d,t] | s ∈ S, d ∈ D, t ∈ T}

Where:

- S = Set of staff (s1, s2, ..., sn)
- D = Set of dates in the period (d1, d2, ..., dm)
- T = Set of shift types {WORK, OFF, EARLY, LATE}

Domain:

D(shifts[s,d,t]) = {0, 1} (Boolean)

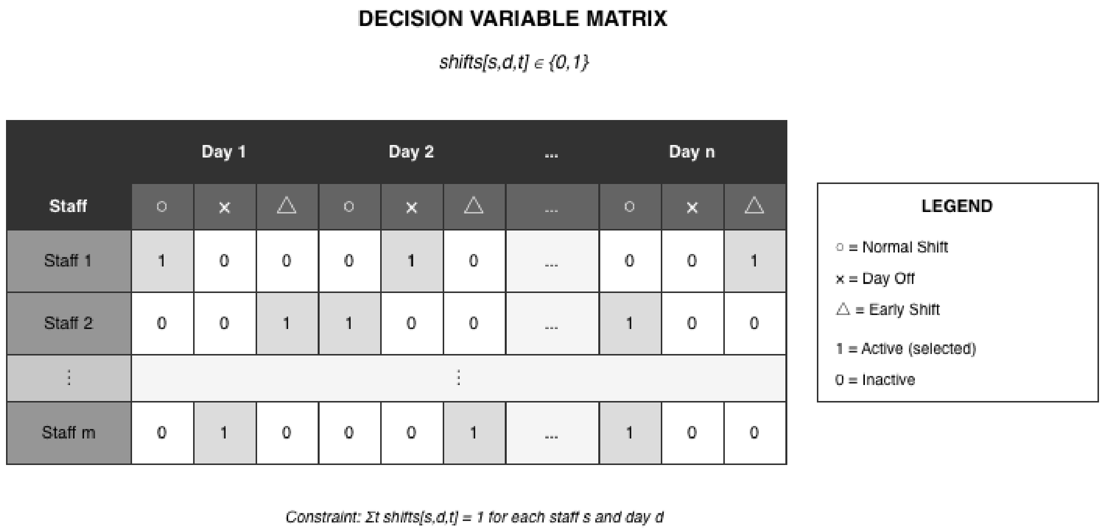
- Value 1 = Staff s gets shift type t on date d
- Value 0 = Staff s does NOT get shift type t on date d

Total Variables:

|X| = |S| × |D| × |T|

Example: 15 staff × 60 days × 4 types = 3,600 boolean variables

3.2.3 Variable Model Visualization


DECISION VARIABLE MATRIX

shifts[s,d,t] ∈ {0,1}

	Day 1			Day 2			...	Day n		
Staff	○	×	△	○	×	△	...	○	×	△
Staff 1	1	0	0	0	1	0	...	0	0	1
Staff 2	0	0	1	1	0	0	...	1	0	0
⋮					⋮					
Staff m	0	1	0	0	0	1	...	1	0	0

Figure 3.2: Decision Variable Matrix Structure

Figure 3.2: Decision Variable Matrix Structure

3.3 Constraint Classification: Hard vs Soft

3.3.1 Soft Constraint Optimization Approach

Unlike traditional scheduling systems that use *hard constraints* (must be 100% satisfied), this research adopts a *Soft Constraint Optimization* approach inspired by the work of Verfaillie & Jussien (2005) and Rossi et al. (2006).

Advantages of Soft Constraints:

1. **Always-Feasible Solutions**: Always produces a solution, never INFEASIBLE
2. **Trade-off Optimization**: Enables compromise between conflicting constraints
3. **Real-world Applicability**: More suitable for actual hotel operational conditions

3.3.2 Constraint Classification Table

Table 3.2: Constraint Classification

No	Constraint	Type	Description	Penalty
1	One Shift Per Day	HARD	Each staff has only 1 shift type per day	-
2	Pre-filled Cells	HARD	Cells already filled by manager do not change	-
3	Calendar Must-Off	HARD	Mandatory off dates (holidays)	-
4	Staff Group	SOFT	Maximum 1 member off/early per group per day	100
5	Daily Limit Min	SOFT	Minimum staff off per day	50
6	Daily Limit Max	SOFT	Maximum staff off per day	50
7	Monthly Limit	SOFT	Min/max off days per staff per period	80
8	5-Day Rest	SOFT	Maximum 5 consecutive work days	200
9	Staff Type Limit	SOFT	Limit per staff type	60
10	Adjacent Conflict	SOFT	Avoid certain sequential patterns	30

3.3.3 Constraint Hierarchy Diagram

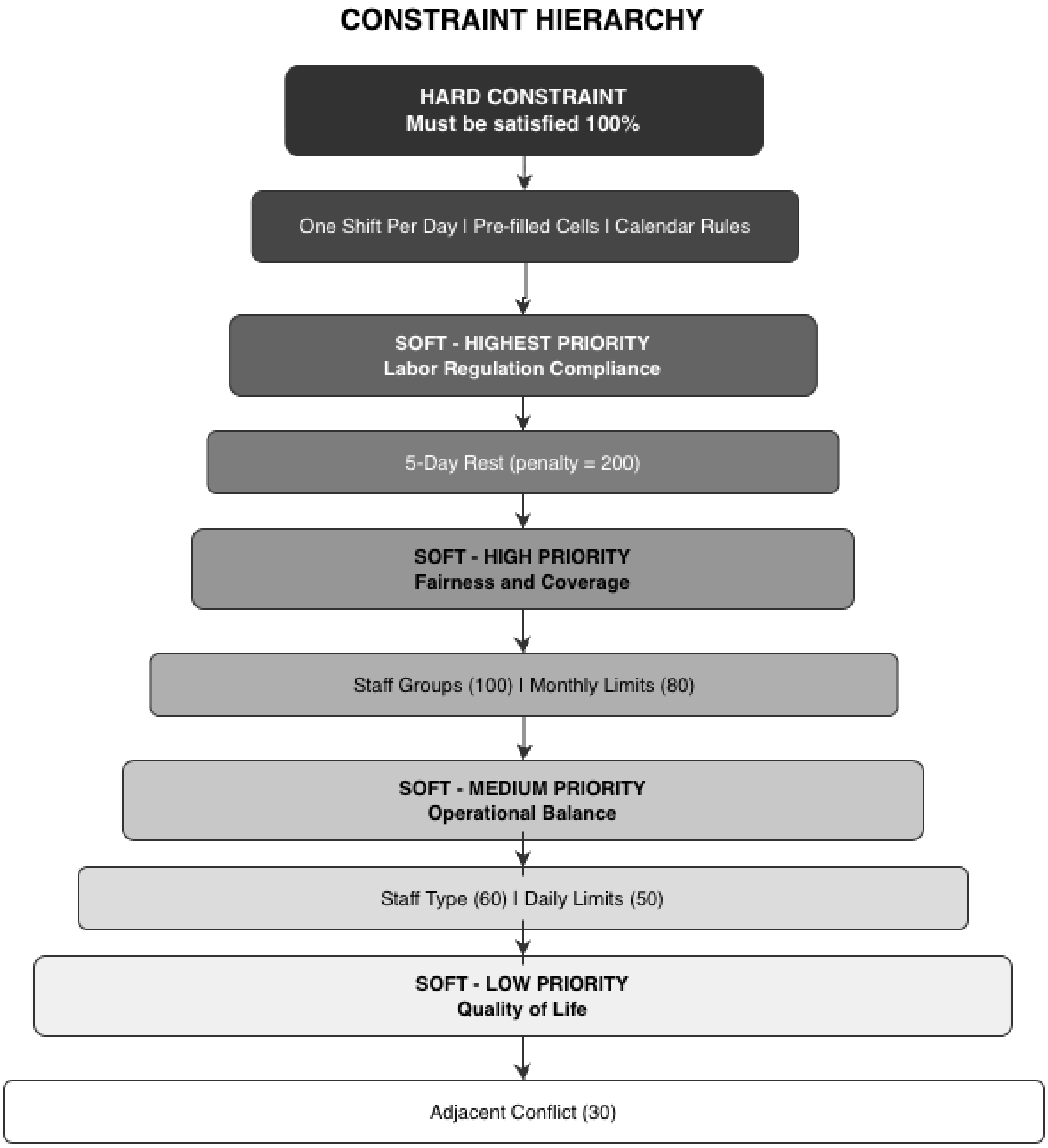


Figure 3.3: Constraint Hierarchy by Priority

Figure 3.3: Constraint Hierarchy by Priority

3.4 Objective Function Formulation

3.4.1 Objective Function

Based on the penalty-based optimization approach from Hooker (2007), the objective function is formulated as total penalty minimization:

Minimize: $Z = \Sigma(w_i \times v_i)$ for all i in V

Where:

- V = Set of soft constraint violations
- w_i = Penalty weight for violation i

- v_i = Boolean variable (1 if violation occurs, 0 otherwise)

3.4.2 Implementation in OR-Tools CP-SAT

Implementation of the objective function in Python using OR-Tools CP-SAT:

```python
def _add_objective(self):
    """
    Build the objective function: Minimize total weighted violations.
    """
    if not self.violation_vars:
        return

    objective_terms = []
    for violation_var, weight, description in self.violation_vars:
        objective_terms.append(violation_var * weight)

    self.model.Minimize(sum(objective_terms))
```

3.4.3 Default Penalty Weights Configuration

Table 3.3: Default Penalty Weights Configuration

Constraint	Penalty Weight	Priority
staff_group	100	High - group coverage important
daily_limit	50	Medium - daily balance
daily_limit_max	50	Medium - maximum daily limit
monthly_limit	80	High - monthly fairness
adjacent_conflict	30	Low - comfort
5_day_rest	200	Very high - regulatory compliance
staff_type_limit	60	Medium-high - coverage per type
backup_coverage	500	Highest - operational continuity

3.5 CP-SAT Solver Architecture

3.5.1 About Google OR-Tools CP-SAT

CP-SAT (Constraint Programming - Satisfiability) is a hybrid constraint solver developed by Google. According to official Google OR-Tools documentation (2024) and Perron & Furnon (2023), CP-SAT combines:

1. **Constraint Programming (CP)** - Domain propagation and inference
2. **SAT Solving** - Boolean satisfiability techniques
3. **Linear Programming (LP)** - Relaxation and cutting planes
4. **Local Search** - Large Neighborhood Search (LNS)

3.5.2 Solver Architecture Diagram

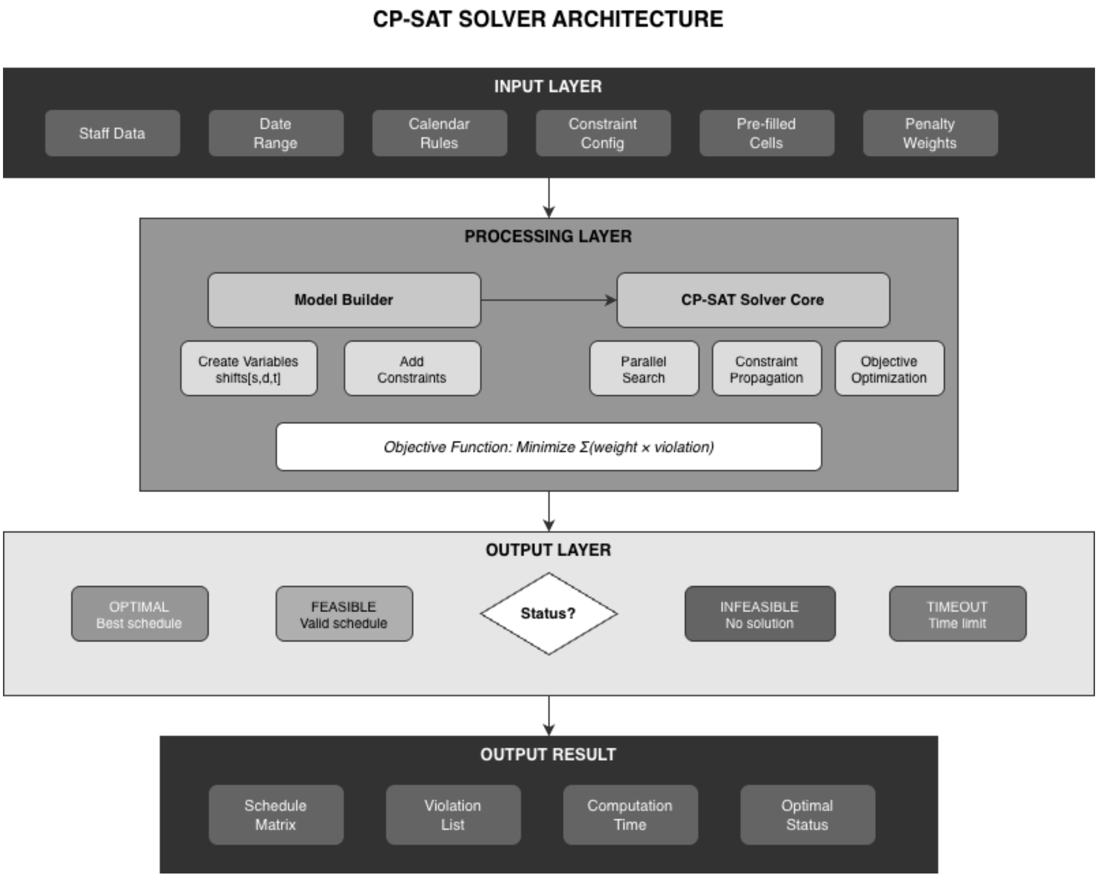


Figure 3.4: Google OR-Tools CP-SAT Solver Architecture

Figure 3.4: Google OR-Tools CP-SAT Solver Architecture

3.5.3 Solver Configuration

Table 3.4: CP-SAT Solver Configuration

Parameter	Default Value	Description
max_time_in_seconds	30	Maximum search timeout

Parameter	Default Value	Description
num_search_workers	4	Number of parallel workers
log_search_progress	True	Search progress logging

3.6 Overall System Architecture

3.6.1 System Architecture Diagram

The shift scheduling system consists of four main integrated layers: User Interface Layer (React + Tailwind CSS), Application Layer (React Hooks + State Management), Optimization Service Layer (Python Flask + OR-Tools), and Data Layer (Supabase PostgreSQL).

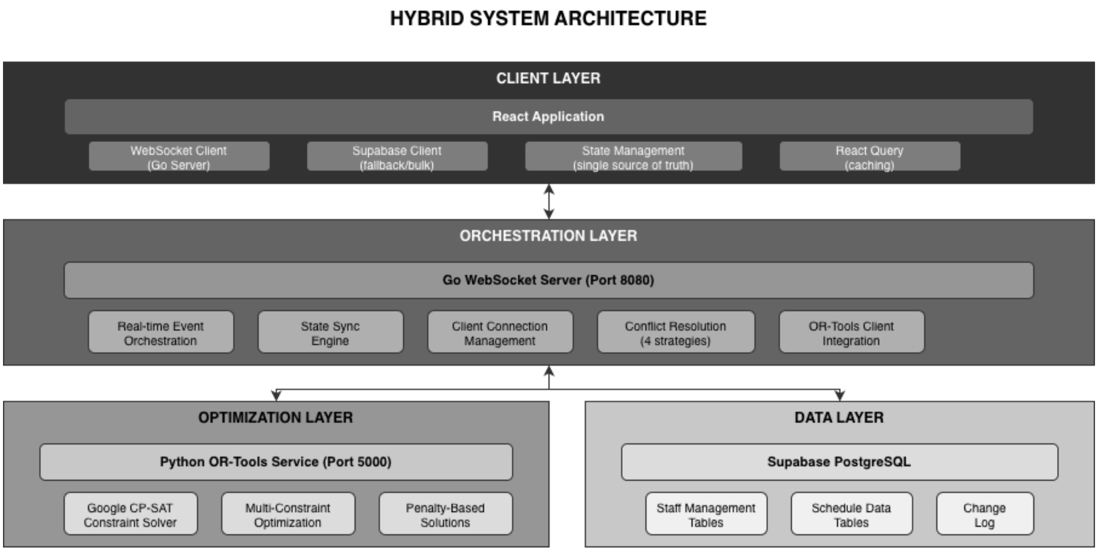


Figure 3.5: Shift Scheduling System Architecture

Figure 3.5: Shift Scheduling System Architecture

3.7 Data Collection

3.7.1 Data Sources

Research data was obtained from a real case study of a hotel kitchen division with the following characteristics:

Table 3.5: Research Data Characteristics

Aspect	Detail
Location	4-5 star hotel

Aspect	Detail
Division	Kitchen/Culinary
Number of Staff	15-20 people
Data Period	January - December 2024
Staff Types	Permanent, Contract, Part-time

3.7.2 Types of Data Collected

DATA COLLECTION MATRIX

Category	Data Type	Method	Source	Purpose
PRIMARY	• Kitchen staff list • Operational rules • Mandatory holidays • Current shift patterns	Interview Observation Documentation	Hotel Kitchen Manager	Problem domain understanding, constraint definition, business requirement validation
SECONDARY	• Labor regulations • Optimization literature • OR-Tools documentation • CSP best practices	Literature Study Technical Documentation	Scientific Journals Google Documentation	Theoretical foundation, algorithm selection, solver parameter configuration
TECHNICAL	• Computation time • Objective value • Solver status • Violation list	System Logs Performance Metrics	CP-SAT Solver	Algorithm efficiency evaluation, solution quality analysis, parameter optimization
VALIDATION	• UAT results • User feedback • Satisfaction scores • Issue reports	UAT Questionnaire Observation	End Users	User acceptance verification, improvement identification, utility validation

Figure 3.6: Data Collection Matrix

Figure 3.6: Data Collection Matrix

3.8 Evaluation Methods

3.8.1 Quantitative Evaluation Metrics

Table 3.6: Quantitative Evaluation Metrics

No	Metric	Formula	Target
1	Constraint Satisfaction Rate	(Total - Violations) / Total × 100%	>= 95%

No	Metric	Formula	Target
2	Hard Constraint Satisfaction	Hard satisfied / Total hard × 100%	100%
3	Soft Constraint Satisfaction	Soft satisfied / Total soft × 100%	>= 85%
4	Computation Time	Time from input to output	<= 30s
5	Solution Quality Score	1 - (Total penalty / Max penalty)	>= 0.9
6	Fairness Index	Std deviation of off days among staff	<= 2 days

3.8.2 Qualitative Evaluation Metrics

Table 3.7: Qualitative Evaluation Metrics

No	Aspect	Measurement Method
1	User Satisfaction	Likert scale questionnaire 1-5
2	Ease of Use	System Usability Scale (SUS)
3	Perceived Fairness	Interview with staff
4	Manager Acceptance	Focus Group Discussion

3.8.3 Comparison with Baseline Methods

Table 3.8: Scheduling Method Comparison

Aspect	Manual	Rule-based	CP-SAT (Proposed)
Creation time	4-8 hours	5-10 minutes	< 30 seconds
Optimality	Not guaranteed	Heuristic	Mathematically optimal
Constraint handling	Trial-and-error	Sequential	Simultaneous
Scalability	Not scalable	Limited	Highly scalable

Aspect	Manual	Rule-based	CP-SAT (Proposed)
Consistency	Varies	Consistent	Optimal & consistent

3.9 Constraint Implementation in Code

3.9.1 Basic Constraint: One Shift Per Day

Implementation of the basic constraint ensuring each staff has only one shift type per day:

```
def _add_basic_constraints(self):
    """Each staff has exactly one shift type per day."""
    for staff in self.staff_members:
        for date in self.date_range:
            self.model.AddExactlyOne([
                self.shifts[(staff['id'], date, shift)]
                for shift in range(4)  # WORK, OFF, EARLY, LATE
            ])
```

3.9.2 Soft Constraint: Staff Group

Implementation of soft constraint for staff groups with the off-equivalent concept:

```
def _add_staff_group_constraints(self):
    """Maximum 1 member from each group can be off OR early per day."""
    for group in self.staff_groups:
        for date in self.date_range:
            violation = self.model.NewBoolVar(
                f'group_violation_{group["id"]}_{date}'
            )

            off_equivalent = sum(
                2 * self.shifts[(s['id'], date, self.SHIFT_OFF)] +
                self.shifts[(s['id'], date, self.SHIFT_EARLY)]
                for s in group['members']
            )

            self.model.Add(off_equivalent <=
        2).OnlyEnforceIf(violation.Not())

            self.violation_vars.append(
                (violation, self.PENALTY_WEIGHTS['staff_group'],
                 f'group_{group["id"]}_{date}')
            )
```

3.9.3 Soft Constraint: 5-Day Rest

Implementation of constraint to ensure maximum 5 consecutive work days:

```
def _add_5_day_rest_constraint(self):
    """Maximum 5 consecutive work days."""
    for staff in self.staff_members:
        for i in range(len(self.date_range) - 5):
            violation = self.model.NewBoolVar(f'5day_{staff["id"]}_{i}')

            work_days = sum(
                self.shifts[(staff['id'], self.date_range[i+j],
        self.SHIFT_WORK)]
                for j in range(6)
            )

            self.model.Add(work_days <= 5).OnlyEnforceIf(violation.Not())

            self.violation_vars.append(
                (violation, self.PENALTY_WEIGHTS['5_day_rest'],
                 f'5day_{staff["id"]}_{i}')
            )
```

3.10 Optimization Process Flow

3.10.1 Optimization Process Flowchart

The optimization process starts from data input (staff, dates, constraints, pre-filled), followed by CP-SAT model initialization, decision variable creation, constraint addition (hard and soft), objective function construction, solver configuration, solver execution, and solution extraction.

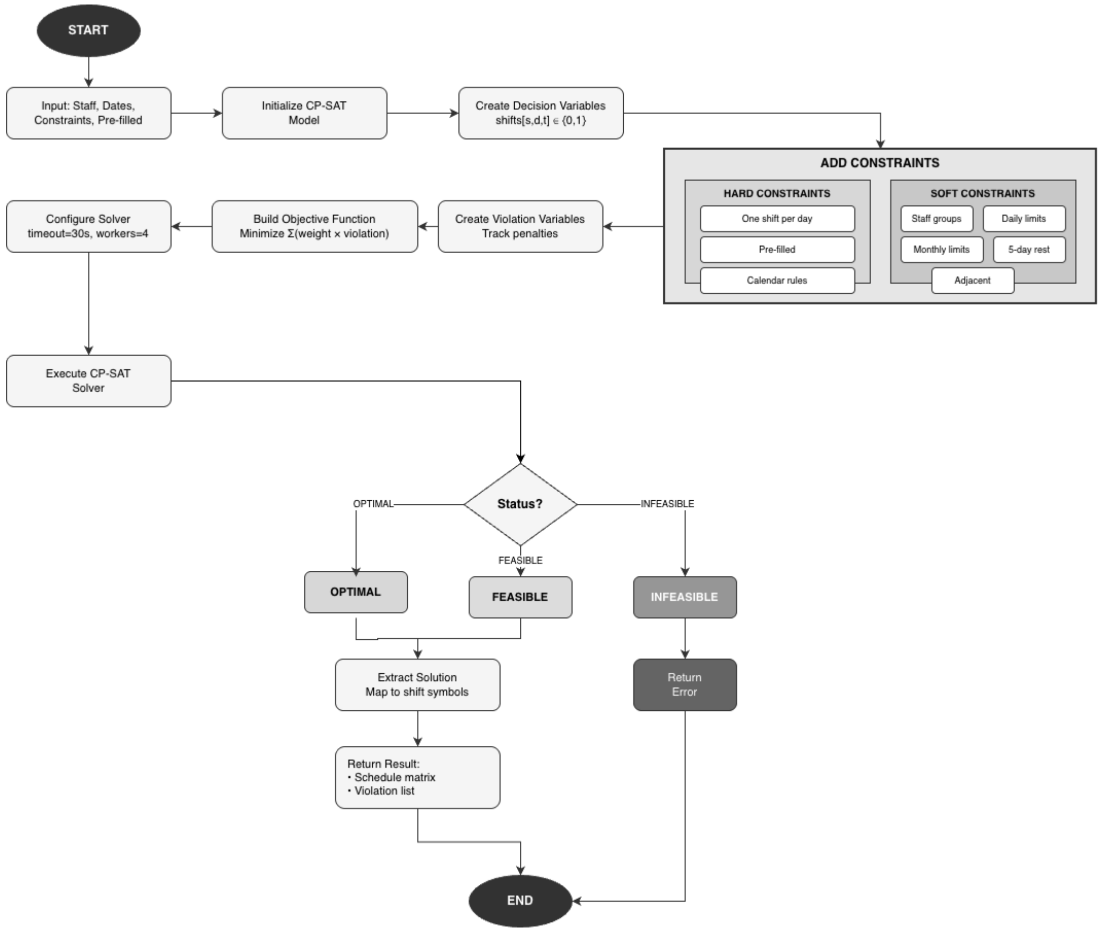


Figure 3.7: Optimization Process Flowchart

Figure 3.7: Optimization Process Flowchart

3.11 Validation and Verification

3.11.1 Testing Strategy

The testing strategy follows a testing pyramid consisting of Unit Tests (testing individual constraint functions), Integration Tests (API + Solver testing), and End-to-End Tests (browser automation).

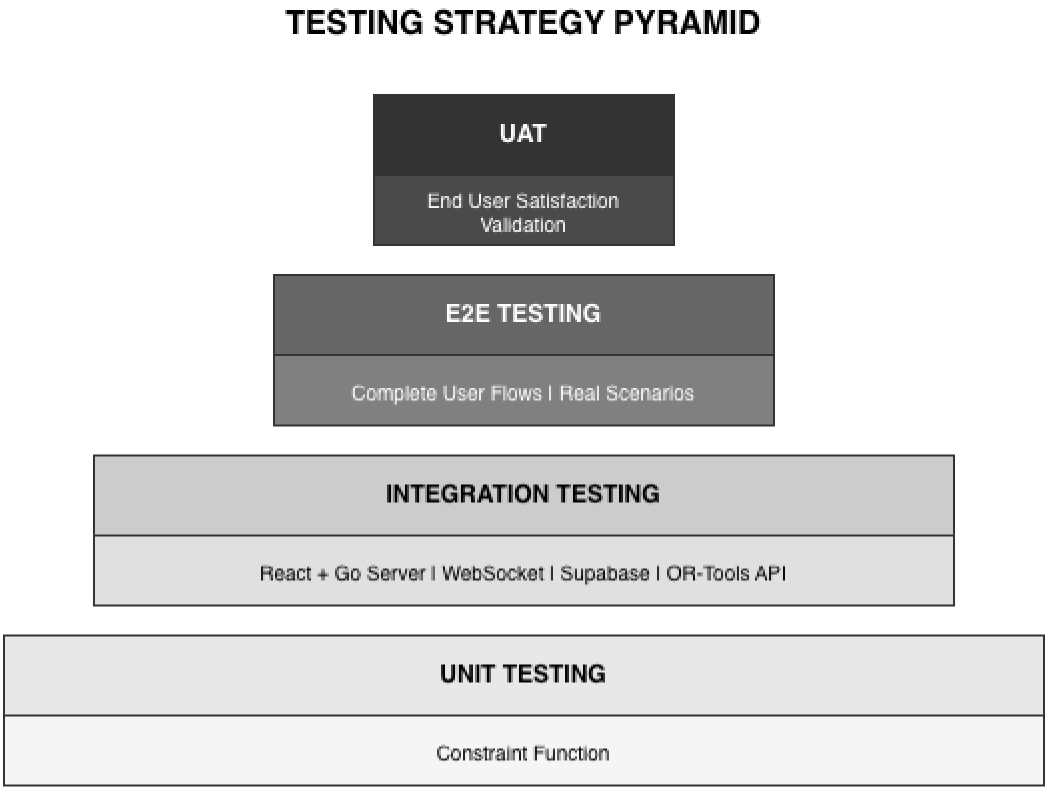


Figure 3.8: Testing Strategy Pyramid

Figure 3.8: Testing Strategy Pyramid

3.11.2 Test Cases

Table 3.9: Test Cases

ID	Test Case	Input	Expected Output
TC01	Basic constraint	5 staff, 7 days	Each staff has 1 shift/day
TC02	Pre-filled preservation	Pre-filled × day 1	× preserved in output
TC03	Staff group constraint	2 members in group	Max 1 off per day
TC04	5-day rest constraint	7 consecutive days	At least 1 rest in days 1-6
TC05	Monthly limit	Min=8, Max=10	Output has 8-10 off days
TC06	Large scale performance	20 staff, 60 days	Solution in < 30s

3.12 Research Schedule

Table 3.10: Research Schedule

Phase	Activity	Duration
Phase 1	Literature study & requirements analysis	4 weeks
Phase 2	CSP model design & constraint mapping	3 weeks
Phase 3	OR-Tools optimizer implementation	4 weeks
Phase 4	UI integration & testing	3 weeks
Phase 5	Evaluation & result analysis	2 weeks
Phase 6	Report writing & revision	4 weeks

3.13 References

Academic References

[1] Hevner, A. R., March, S. T., Park, J., & Ram, S. (2004). Design Science in Information Systems Research. MIS Quarterly, 28(1), 75-105.

[2] Peffers, K., Tuunanen, T., Rothenberger, M. A., & Chatterjee, S. (2007). A Design Science Research Methodology for Information Systems Research. Journal of Management Information Systems, 24(3), 45-77.

[3] Russell, S. J., & Norvig, P. (2020). Artificial Intelligence: A Modern Approach (4th ed.). Pearson.

[4] Rossi, F., Van Beek, P., & Walsh, T. (2006). Handbook of Constraint Programming. Elsevier.

[5] Verfaillie, G., & Jussien, N. (2005). Constraint Solving in Uncertain and Dynamic Environments: A Survey. Constraints, 10(3), 253-281.

[6] Hooker, J. N. (2007). Integrated Methods for Optimization. Springer.

[7] Krupke, D. (2024). CP-SAT Primer: Using and Understanding Google OR-Tools' CP-SAT Solver. TU Braunschweig.

[8] Van Den Bergh, J., Belien, J., De Bruecker, P., Demeulemeester, E., & De Boeck, L. (2013). Personnel Scheduling: A Literature Review. European Journal of Operational Research, 226(3), 367-385.

[9] Burke, E. K., De Causmaecker, P., Berghe, G. V., & Van Landeghem, H. (2004). The State of the Art of Nurse Rostering. Journal of Scheduling, 7(6), 441-499.

[10] Ernst, A. T., Jiang, H., Krishnamoorthy, M., & Sier, D. (2004). Staff Scheduling and Rostering: A Review of Applications, Methods and Models. European Journal of Operational Research, 153(1), 3-27.

Technical References

[11] Google OR-Tools Documentation (2024). CP-SAT Solver Guide. https://developers.google.com/optimization/cp/cp_solver

[12] Google OR-Tools GitHub Repository (2024). Constraint Programming Examples. https://github.com/google/or-tools

[13] Perron, L., & Furnon, V. (2023). OR-Tools by Google. Operations Research Tools. https://developers.google.com/optimization

[14] Flask Documentation (2024). Flask Web Framework. https://flask.palletsprojects.com/

[15] React Documentation (2024). React: A JavaScript Library for Building User Interfaces. https://react.dev/