Multi-Industry Staff Scheduling Under Labor Law Constraints Using MILP, CP and Genetic Algorithms

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Multi-Industry Staff Scheduling Under Labor Law Constraints Using MILP, CP and Genetic Algorithms

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Abstract

Staff scheduling is always a difficult problem in any sector due to fluctuating demand, different shift patterns, and strict labor laws. This research developed an optimization framework that generates weekly roasters for staff using three different models: Mixed Integer Linear Programming, Genetic algorithm, and Constraint programming. The research integrated demand forecasting, availability of employees, and constraint formulation based on industry. The output was evaluated using nine different metrics which gave result in MILP having a good staffing demand but also it included overstaffing, CP assigned very few shifts indicated understaffing and GA gave a balanced and realistic staff schedule. The study concluded GA was the most compliant and scalable method for large multi domain staff scheduling tasks, while MILP exceeds demand fulfilling and CP is not capable of handling large data.

Keywords: staff scheduling, multi-industry, optimization, MILP, CP, Genetic Algorithm, labor regulations

1 Introduction

1.1. Background

The problem is about staff roaster scheduling in restaurant, healthcare and retail industries was recognized as a difficult, demanding and complex task. Many times, these industries were noticed to endure challenges in fairly scheduling the shifts while following the Irish labour laws. Earlier work had illustrated that staff scheduling was generally managed by either rule-based systems or manual works, which usually resulted in discontent and inefficiency (Gusmeroli & Bettinelli, 2024).

1.2. Motivation

Due to poor roasters were described to cause legal non-compliance, understaffing and workplace exhaustion it was important to study staff scheduling for restaurant, retail and healthcare (Gusmeroli & Bettinelli, 2024). Similarly, some challenges also had been reported in healthcare sector, where for improving efficiency and fairness optimization-based approaches were found for staff scheduling (Gerlach et al. 2023). Different variables were used to get the output of staff roaster scheduling, Primary input factor was staff availability, while skill level and requirements of role were essential factors for allocation of shift. Employee satisfaction and distribution of workload were the outcome variable for fairness also mandatory rest periods and maximum weekly hours were assumed to affect legal compliance. So far, these problems affecting the staff scheduling for the multi-sector industry using optimization techniques have been seen as unresearched but suitable for such methods.

1.3. Research Question and Objectives

Taking forward the future research delineated by Gusmeroli and Bettinelli (2024)—who referred to the horizon of not-too-large, dynamic environments for MILP-based scheduling models—and the Gerlach et al. (2023) study, where they proposed extending fairness-prioritising constraint models to high-variability, real-time settings, this work extends to other requirements such as dynamic weekly availability, small-team scheduling, and stringent labour-law compliance. The consequent research question formulated was:

"How effectively can optimization techniques such as Constraint Programming, Genetic Algorithms and Mixed Integer Linear Programming (MILP) generate multi-industry staff scheduling as per the roles, availability under Irish Labour law constraints?"

1.4. Research Objectives:

The main goal is to evaluate compliance with legal laws, measure transparency, preference, unmet demand, oversupply metrics and fairness in shift scheduling and compare different optimization techniques.

1. To plan and establish a standardized workforce planning model that will be used in restaurants, retail, and healthcare sectors.
2. To decide which method, MILP, CP-SAT, or Genetic Algorithms, are the most effective in creating fair, legally conforming and preference- based staff schedules.
3. To create a demand-forecasting and availability-generation pipeline that can be used to schedule the next week subject to labour-law considerations.
4. To measure the results of scheduling with quantitative measures of unmet demand, breach of contracts in terms of hours, equitability, and satisfaction of employees.

1.5. Summary

The contribution of this work was look forward to exploring AI based optimization shift scheduling research into multi-industry sector. The comparison of given three different optimization techniques was based on Irish labour rules and regulations such as minimum break times or rest periods also maximum weekly ours depend on part-time or full-time position. The study was also focused on identify trade-offs between computational efficiency, transparency fairness and solution quality.

1.6. Limitations

The high-degree of synthetic availability information, as well as the simplified demand-forecasting model, limits this study because it does not necessarily reflect the unpredictable real-life variations in staffing requirements. It is also dependent on already established shift templates which might inhibit flexibility within industries. The key hypothesis is that all three models MILP, CP-SAT, and GA will be able to produce legal and fair rosters, although the effectiveness of each of them will depend on the magnitude of the problem and the complexity of constraints. It is presumed in the research that historical data is precise, job descriptions of employees are constant over the planning timeframe, that both the regulations of the contract, labour laws, and shift schedules defined and are uniformly followed.

The outlining this report was structure as follows. Sections 2 go through the related work covering existent staff scheduling approaches in different sectors. Section 3 reviews the research methodology which included collection of data, experimental design, implementation of model and evaluation procedure. Section 4 provided the specifications of design, detail about techniques and requirements used for implementation of solution. Section 5 demonstrated the process of model implementation and output produced by it. Section 6 presented evaluation results which includes experiments, discussion and statical analysis. Lastly section 7 completed the research by summarizing the objectives, key findings and suggesting the directions and limitation for future work.

2 Related Work

The main aimed of this literature review is to establish the given research within similar studies based on optimization techniques and staff roaster scheduling. Earlier work in this field was analysed to understand the strengths, weakness and improvement in the areas which are related to restaurant shift roaster scheduling. The study covers shift scheduling based on optimization techniques including healthcare, retail and hospitality with fairness, efficiency and legal compliance.

2.1 Healthcare/ Nurse Scheduling

1. A Hybrid Genetic Algorithm for Nurse Scheduling Problem Considering the Fatigue Factor – Amindoust et al. (2021) This paper proposes a combined GA model that directly involved nurse fatigue, through penalties against the long shifts and cumulative shifts. Its strength was that it realistically considers the human factors of COVID-19, demonstrating that the GA can consider such soft constraints as fatigue and preferences. The weakness of the study was that the findings are limited to one case analysis of a hospital, and this can be a limitation in generalization. This approach was what drives GA fitness functionality of punishing over-hours and lack of rest and rewarding preference satisfaction.

2. A Hybrid Fix-and-Optimize and Simulated Annealing Algorithm for the Nurse Rostering Problem – Turhan et al. (2020) To address large real-life instances of nurse rostering Turhan and others suggest a hybrid metaheuristic based on fix-and-optimize that incorporates simulated annealing. Its key advantage was to find ideal solutions at decent computation times on challenging benchmarks. However, the model was specialized and more difficult to implement as compared to standard MILP or GA models. In comparison to this, current research could employ evaluation measures against exact (MILP) and CP-SAT techniques.

3. Optimizing Nurse Rostering: A Case Study Using Integer Programming – Mystakidis et al. (2024) In this paper, Mixed Integer Programming was applied to a real-life hospital, and the results prove that MIP could capture a variety of objectives including coverage, fairness and preferences. It has a strong point in the form of detailed case study and clear modelling of labor regulations. The restriction was scalability: finishing the very large instances was difficult and the paper suggests the necessity of decomposition or heuristics. Current MILP module is an extension of this concept to three industries but cuts off on the number of constraints to manage more than 1,000 employees.

4. Using OR-Tools When Solving the Nurse Scheduling Problem – Oliveira, Rocha & Alves (2024) Oliveira et al. demonstrated that the Google OR-Tools CP-SAT solver may be applied to perform nurse scheduling by focusing on modelling flexibility and performance of the solver. The main strength was that CP-SAT is effective in solving complicated logical conditions and huge solution spaces. The article, however, involved no industry generalization but only healthcare. CP-SAT scheduler is based on the same as a tool but dialogues restaurant and retail and a single common code base.

5. An Intelligent Optimization Strategy for Nurse–Patient Scheduling in IoMT – Harb et al. (2024) Harb and colleagues combined genetic algorithms with IoMT data in dynamically assigning nurses to patients. Herein lies the possibility to integrate real-time sensor and optimization approaches. One of them is the high data and infrastructure requirements, which might be lacking in smaller hospitals. However, in this paper, shown that there are some opportunity extensions that may include real-time demand signal.

6. A Multi-Objective Genetic Algorithm for Healthcare Workforce Scheduling – Patel et al. (2025) Patel presented a multi-objective GA that would optimize on both the labor cost and the coverage and satisfaction of the staff in a hospital unit. It has the strength of making a Pareto set of solutions instead of a plan giving managers options on trade-offs. The consequence was the complexity of the schedule's interpretation and choice between a variety of non-dominated schedules. Given GA has a less complex design of single though the concept of cost-demand-satisfaction is highly driving in motivation of fitness structure.

7. Integrating Nurse Preferences into AI-Based Scheduling Methods – Renggli et al. (2025) Renggli et al. came up with a framework that elicits nurse preferences in a systematic manner and incorporates them into AI scheduling. Its human-centered approach to collecting qualitative and quantitative preference information is its primary strength. Nevertheless, the paper didn't apply a complete optimization engine but concentrated on design principles. Related ideas were represented in current research as the numerical field preference score operationally which assigns a greater strength in all three algorithmic modes to higher-preference jobs and full-time contracts.

8. Exploring Nurse Perspectives on AI-Based Shift Scheduling for Fairness, Transparency, and Work-Life Balance - Gerlach et al. (2023) explored the perception of nurses regarding AI-based scheduling applications based on the aspects of fairness, transparency, and work-life balance. The paper has a strength of qualitative analysis centered on the users, which identifies the practical issues like trust and acceptance. The main shortcoming, however, was the fact that it didn't give a complete functioning scheduling algorithm since it just gave insights into what users expect.

2.2 Retail Staff Scheduling

9. Employee Scheduling Problem for a Retail Store with Multiple Product Categories – Apak (2022) Apak develops a real retail store problem and scheduling issue in which employees were designed in various product categories and shifts. The principal strength was the modelling of multi-role staff and its influence on sales performance. The paper, however, primarily used integer programming and fails to compare the approach with the use of heuristics. Current data also has many different industries and positions but was more contract type/availability-oriented rather than category sale-oriented.

10. Real-Time Bi-Objective Personnel Re-Scheduling in the Retail Industry – Hassani et al. (2021) Hassani and others came up with a real-time, fast heuristic of modifying retail schedules in the presence of small disruptions. The strength was bi-objective perspective which balances the cost of labor with the number of changes of shift. The drawback was that only re-scheduling was taken into consideration and the model was specific to a particular retailer. Current practice was weekly planning vs. real-time repair though the concept of bi-objective performance dictates the metrics of evaluation unmet demand and oversupply.

11. Improving the Robustness of Retail Workforce Management with a Labor Flexibility Strategy – Porto et al. (2025) Porto suggested a two-phase stochastic model of optimization including the elements of multiskilling and the uncertain demand in the retail personnel planning. The advantage was clear management of uncertainty and flexible hours which resulted in stronger schedules. However, the model itself was mathematically cumbersome and is aimed at strategic planning and not at weekly rostering. The approach given currently was deterministic, though it could be generalized to the use of similar stochastic concepts in future research.

12. Labor Planning and Shift Scheduling in Retail Stores Using Customer Traffic Data – Ma et al. (2024) combined the customer traffic forecasts and labor planning applying mixed-integer programming and constraint programming to construct demand-based schedules. This fact-driven method is one of the evident strengths since it shows how external demand signals enhance the quality of staffing. The constraint was dependent on accurate traffic histories which might be difficult to acquire in smaller outlets. The same principle inspired more basic demand model on weekdays and applies only to the assigned staff in the past and not to the number of customers.

13. Pareto-Optimal Workforce Scheduling with Worker Skills and Preferences – İşeri, Güner & Güner (2025) The scheduling of service workforce among the different skills and preferences in the scheduling of the workforce is discussed in this paper. The strength was given in the form of subtle modulation of heterogenous workers and customer demand. The weaknesses where smaller firms might be constrained by the complexity of implementation and the calculation time. Given model offered to encode skill/preference indirectly using staff role and preference score.

14. A Binary Integer Linear Programming Model for Employee Scheduling in a Convenience Store: A Case Study in Nakhon Pathom – (2025) A binary integer linear programming model of the convenience store staffing was given here, where the consecutive working days and the minimum rest were constrained. Its strength was realistic full-specified case with operational constraints. Its drawback was that it only optimizes one small store and didn't consider the preferences of the employees.

15. AI-Powered Retail Workforce Scheduling – Shyft (2025) This described how this retail scheduling automation with AI may handle the intricate processes of skill, availability, and changing demand. The primary strength should be the focus on real-time changes and mobile integration of employees. The article was advanced and didn't reveal any underlying models and restrictions.

16. Labor Management in the 2020s: Advanced Labor Planning and Modern Scheduling Practices – Logile (2024) here the authors have explained the roles of contemporary labor planning tools and scheduling as a way which retailers can make use of in achieving flexibility and compliance. Its advantage was the practical recommendations on

implementing advanced optimization. Its weakness was the fact that it's not an empirical study that is carried out formally. Given research able to fill this gap with the help of concrete optimization models and empirical evaluation metrics based on real like data.

17. A Mixed-integer Linear Program to Create the Shifts in a Supermarket - Nicolò Gusmeroli & Andrea Bettinelli (2024) aimed at producing the shifts of the employees in the supermarket, considering labor needs, legal regulations, and personnel availability. One of its key benefits was the possibility of adding flexible types of shifts and staffing on a dynamic basis. But its critical weakness was in calculational complexity as it is hard to compute in time as the supermarkets were extremely large and have hundreds of staff to make real-time adjustments.

2.3 Restaurant Staff Scheduling

18. Goal Programming Approach for Service Staff Scheduling Problem in a Restaurant – Inan (2023) research came up with a goal-programming model that involves skills, seniority, preferences and system demand related to the staff in the restaurant. The model paid great attention to working with equal distribution of work, and this is a significant strength. The formulation was, however, complex and could be hard to maintain in case business rules differ frequently.

19. A Binary Integer Programming Model for Personnel Scheduling at a Fast-Food Restaurant – (2023) In this case study, the model based was a binary integer programming in the analysis of post-pandemic scheduling in a popular fast-food restaurant. It demonstrated how optimization to specific levels can save funds and impose minimum shifts staff. This was a drawback as less information said about employee preferences or satisfaction; it was more about cost and coverage. In comparison, given MILP would have both contract restraints and preference ratings, which fit better with human-related scheduling.

20. Shift Scheduling with the Goal Programming Approach in Fast-Food Restaurant: McDonald's in Kelantan – Nasir et al. (2022) authors used goal programming to generate monthly rotations of shifts in one of the branches of McDonalds to balance various goals, including the derivation of demand and equity. It was strong due to its multi-objective and direct implementation into a fast-food setting. The weaknesses were the use of a single restaurant and a limited number of staff. Current MILP and GA models assume a multi-criteria attitude but grow to include over a thousand employees working in three industries.

21. Optimized Job Scheduling for Food Service Staff to Ensure Quality Standards and Minimize Labor Costs – Dutta et al. (2025) a study on job scheduling as it influences quality and labor cost providing an analysis of staff availability, flexibility, shift strategy and training. Its strength was its tendency to unite such statistical analysis and scheduling concepts as relating HR variables to results. The weakness was the fact that the scheduling model was not perfectly formalized as MILP or GA. Current research gave specific optimization algorithms whilst having the same goal of optimizing quality of services and labor cost.

22. Predicting and Planning: An Intelligent System for Demand-Based Hotel Staff Scheduling – Li et al. (online 2025) suggested a smart system of hotel personnel planning based on demand predictions as the way to eliminate last-minute corrections and to increase the quality of services. This showed predictive analytics to supply an optimization engine.

The drawback was that all the details of algorithms were partially obscured in a proprietary system environment.

23. Optimal Scheduling of Waitstaff with Different Experience Levels at a Restaurant Chain – (2025) This study examined the level of experience impacting staff allocation and quality of customer service. Its power was its connection of heterogeneity of staff to the decisions on scheduling. One constraint was that it contains more theoretical insight which was founded on the presumed demand situations. In given model, experience wasn't directly encoded but might be encompassed by the staff-role logic such as long features or in the preference-score.

24. Algorithmic Management in Hospitality: Examining Hotel Employees' Perceptions of AI-Driven HR Systems – Turcinovic (2025) examined the perspectives of hotel employees towards AI-based HR and scheduling systems in the areas of work-life balance, control, and acceptance. Its human and ethical perspective was its strong side as it helped to keep in mind that algorithmic scheduling influences the experience of employees. The weakness was that it didn't put forward specific mathematical models and algorithms. Interpreted metrics of current evaluation process reflect the identical issues by integrating the sense of fairness and law into the layer of optimization.

25. An Evolutionary Method with Shift Pattern Learning for Real-World Irregular Workforce Scheduling – Ma et al. (2025) introduced a machine-learning augmented memetic algorithm which trains on expert shift patterns. This was strong since it acts like human schedulers and came up with solutions that are more readily accepted by the users. Training of such models, however, was time-consuming involving massive historical data and tuning. Current GA is less complicated and more rule guided.

Research Gap

In fields of healthcare, retail and restaurant/hospitality, the existing literature typically deals with a single industry at the time and either exact optimization (MILP/CP) or single heuristics. There were not many works, which refer to a harmonized data model, combine three algorithmic paradigms (MILP, CP-SAT, GA) on a single multi-industry data and confidently compares them with each other, based on the common evaluation scheme and scores, such as unmet demand, over supply, violation of legal limits and satisfaction of interests. Given research filled this gap successfully which was similar with the future works of the above literature reviews.

3 Research Methodology

This study was conducted to implement staff scheduling based on optimization technique for restaurant sector under Irish labour laws. The research methodology followed six key steps such as problem definition, collection of data, data preprocessing, training and testing of model, evaluation and validation of model. Each step was designed to check whether the output could be simulated by other studies with validity and reliability.

3.1. Problem Definition

The study proposed the challenges for staff scheduling in restaurant, retail and healthcare sector which included following Irish labour laws for legal compliance, ensuring employee preference and fairness in shift scheduling process. In the multi-sector domain, staff shift rostering was mostly done manually or by the tools which are rule-based which frequently made staff dissatisfaction, breaking of the labour laws and imbalance in workload. Therefore, this research performed to change the manual staff scheduling into an optimization-based scheduling. Irish labour rules and regulation were evaluated to establish the scheduling system must operate within legal framework. System used the constraints which included the specific clauses from the Organization of Working Time Act (1997, Ireland) given as below:

- Minimum Rest Period: Employees must get at least 11 hours of rest between shifts.
- Maximum Working Hours: Part time employees should not exceed 20 hours per week, and full-time employees should not exceed 48 hours per week.
- Weekend and Overtime Work Rules: Staff allocations on weekend in excessive manner should be avoided to maintain staff satisfaction and overtime should be adjusted fairly.
- Weekly Rest Day: Each employee must get minimum of one rest day per week.

These all-legal compliances were addressed as constraints sets in mathematical format that any schedule must get generate correctly. Also, fairness part was integrated by balancing weekend duties and minimizing deviations in total weekly hours. Therefore, problem was defined as multi-objective optimization task where the main goal was to generate the staff schedules which show fairness, minimize labour law violations and get correct shift for each staff.

3.2. Dataset Preparation

This process was design by following strict ethical research standard to find the operational workforce of restaurant sector. Data were collected from the restaurant by obtaining the permission through email consent from management and staffs to use staff availability and shift records ensuring compliance with institutional ethical guidelines. The dataset contains past six months of staff rostering data which includes staff availability, roles, assigned shift and working hours. This dataset provided real world data which would practically be accurate for optimization-based modelling. To improve generalizability and robustness of model by adding two different domain datasets were as below:

- Nurse Rostering Dataset (BMC Nursing, 2025) this would help with fairness constraints and legal compliances for shift scheduling.
- Retail Workforce Scheduling Dataset (Kaggle, 2024) this would present the preference-based shift scheduling in large scale organizations.

These two datasets were merged with primary dataset after cleaning procedure which showed 6372 rows which introduced attributes based on categories such as different domain Restaurant, Healthcare and Retail. This would help to check that model could handle fairness and legal compliance through different sectors while maintaining restaurant staff scheduling.

3.3. Dataset Merging:

Here is the merging of three different sectors for scheduling the staff roaster. We used three different loader functions for three different sectors such as load_restaurant(), load_nurse() and load_retail(). Each loader would perform functions such as reading its own dataset, renaming the columns which are inconsistent, adding the new column industry type, columns containing the contract for the workers based on full time and part time, converting of contract hours, based on contract and role compute the preference score for staff, normalization for date column, if availability is missing then add default one and last check the shift start and end times are in standard format or not.

After merging all three dataset we got totally 6372 rows and 18 unique roles across different sectors. The merge dataset contain the columns such as employee id, staff name, staff role, industry type, contract type, preference score, contract hours, start of availability, end of availability, work start time, work end time, assigned shift or not (0 or 1).

3.4. Data Preprocessing

Data preprocessing steps should be done to check the cleaning and transformation of data from all datasets should be similar before using scheduling methods. Dates were converted to ISO format which is YYYY-MM-DD, using industry-based defaults shift time and missing availability were imputed and based on weekly hours filled the missing contract types. For data consistency roles names and duplicated values were cleaned or removed also to ensure data integrity preference score and contract hours got rechecked. This merge dataset was used as history to train the model.

3.5. Next Week Staff Availability:

It's difficult to go through each staff member to ask about their availability next week as its multi-industry data where restaurant data is from original roasters and the remaining two healthcare and retail data are from Kaggle. This was the reason a synthetic one-week availability dataset was generated for all the industry employees based on their contract type and working patterns. Full-time employees which can do 40 hours per week allotted with 5 working days and part-time employees with 20-hour shifts allotted with 3 working days. This dataset contains all three industries and their employees such as restaurants, healthcare and retail, which produced totally 7455 entries for staff availability which was used to test the scheduling algorithms.

3.6. Demand Forecasting:

For scheduling staff roaster based on their availability for each role and date this method was used where historical shift assigned dataset was analyzed. A pivot table helped to convert roles count on daily basis to time series which made it easy to predict next week's staff demand based on previous data. The demand forecasting gave for each role staffing requirements which used to trained model based on MILP, CP and GA to give correct staffing while reducing understaffing.

3.7. Scheduling Algorithms

Staff Scheduling for three different industry such as restaurant, healthcare and retail was done with the help of three distinct optimization techniques such as MILP, CP and GA. These three models have their own way of handling staff scheduling. MILP would use binary decision variable which maximizes staff preference based on staff availability, contract type and constraints for scheduling. Constraint Programming would use Boolean propagation method for fasted scheduling of the staff by following the rules and regulations, The Genetic Algorithms would use chromosome method which represents potential schedule, daily employee assignments using rewards and penalties to crossover, tournament selection and mutation of feasible schedules.

- **MILP (Mixed Integer Linear Programming):** This model used binary variable for assigning the shift for each employee and day. Its main objective was total preference for each day while following staff availability, weekly hours and day rest, break time constraints. The framework used was PuLP with the CBC solver which helped to schedules based on legal compliance and preference.

- **Constraint Programming:** This model is the same copy of MILP model in a working manner, but it would use Boolean optimization and constraint propagation for improving model performance. The solver was used in this maximized weighted preference score with the help of linear constraints and BoolVar(). Handling of large employee roles efficiently done by OR-Tools.

- **Genetic Algorithm:** The GA used the two main keywords such as chromosomes and genes as per word mentioned genetic. This would schedule staff based on binary chromosomes of length days and employees. Also, there is one fitness function which would penalize contract-hour breaches, failures for rest day, not considering availability and unmet demand while keeping preference score proper. A GA used some other keywords such as crossover which means combining parent schedule to create new one, mutation means random changes in the schedule and tournament selection was to choose fittest parents for the next schedule helped for best staff schedule for an optimization model.

3.8. Evaluation Methodology:

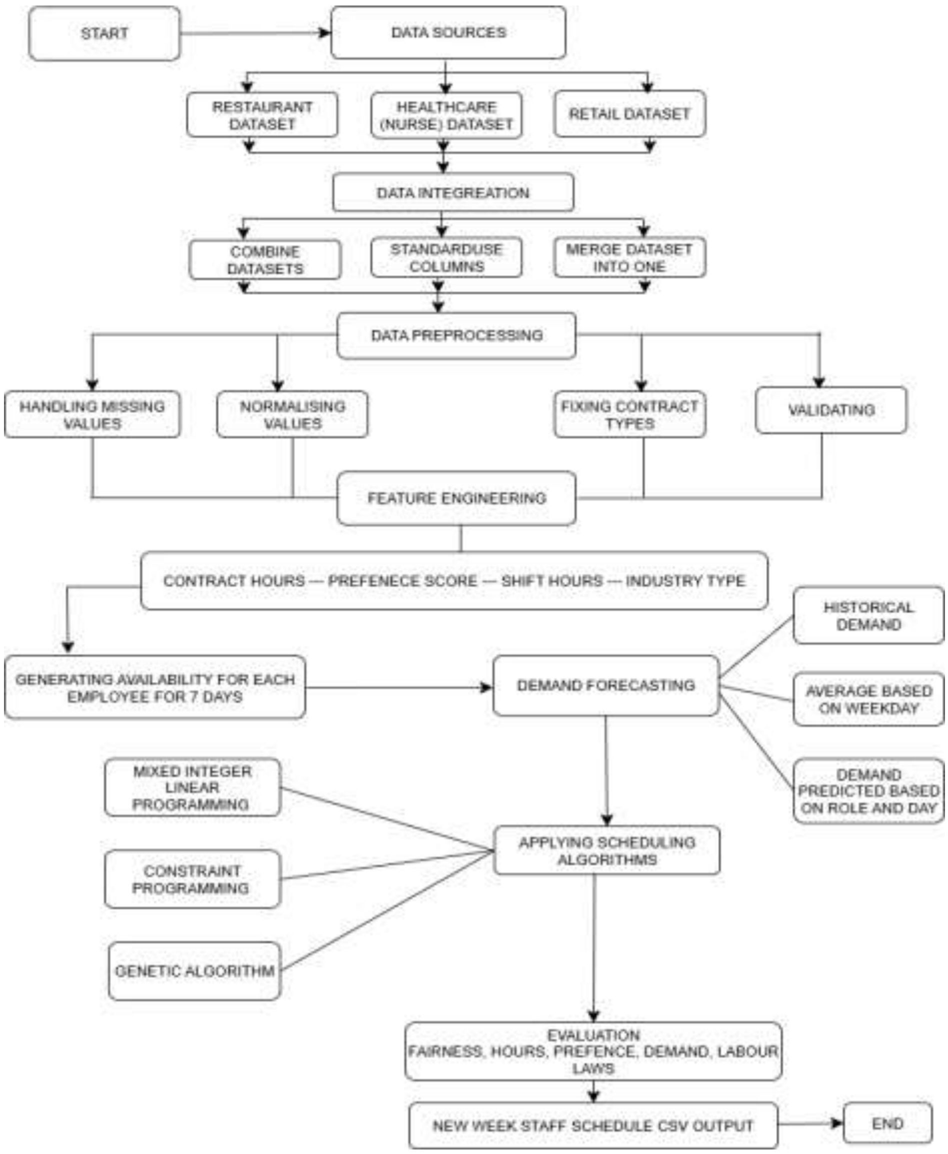
Here we used three different optimization models for staff scheduling such as MILP, CP and GA. They were evaluated based on nine metrics which include availability violations, rest day compliance, contract break, shift counts, and preference score satisfaction. Demand forecasting was evaluated by comparing assigned schedules including staffing based on per day and role. Based on all these metrics three models such as MILP, CP and GA compared to check compliance, fairness and service level efficiency.

4 Design Specification:

The system is designed based on multi-algorithm and modular framework which integrated dataset merging, data preprocessing, generating availability, demand forecasting and optimization techniques to generate staff schedule. The architecture was divided into four different parts: Data Preprocessing step, generating staff next week availability, demand forecasting and Scheduling using optimization models. Each layer would work on clean and structured datasets. This model design check fairness, transparency and reproducibility.

Last step for this architecture contains optimization framework which includes three different scheduling algorithms: Mixed Integer Linear Programming (MILP), Genetic Algorithm (GA) and Constraint Programming (CP-SAT) for scheduling staff based on their availability and the legal constraints. To check fairness through comparison all methods follow same input format such as employee id, their availability and demand forecast. The MILP model computes mathematically optimal staff scheduling with the help of binary decision variable and linear constraints while Constraint Programming schedule based on Boolean constraint propagation to easily find discreate search spaces which was most suitable for large and complex problems. And the last Genetic algorithm went through population-based heuristics which evaluated to get near optimal solutions where each week schedules were denoted as chromosome. Then first evolution for fitness was schedule and history (parents) were denoted as crossover and mutation to create new schedule.

Below is the architecture for the staff scheduling system:



Architecture Diagram for Staff Scheduling

This framework ensures that each algorithm was follow Irish labor-law constraints, employee preference, demand for role for day, contract rules (Full time – 40 hours, Part time – 20 hours). By implementing three different model for staff scheduling through multi – industry domain with the architecture, supports systematic working while managing future work of machine learning based demand prediction and hybrid model for staff scheduling.

5 Implementation

The implementation step was aimed at building a staff scheduling model that would be able to handle different processes such as generating availability patterns, handling different sector data, predicting role base demand and scheduling weekly staff roasters. All the modules were done in Python 3.10 with the help of libraries such as pandas and NumPy to preprocess the data also used three different scheduling algorithms such as MILP by Pulp, CP-SAT with Google OR-Tools, Genetic algorithm with DEAP and final data visualizations. The model was trained and tested in a Jupyter-Notebook.

The implementation included different important outputs in step-by-step manner. In first step, three different sectors such as restaurant, healthcare and retail dataset were merged into a single dataset which can be used as historical dataset. Then data preprocessing step occurred where values got normalized, cleaned and converted into the correct format. In second step, staff availability for 7 days created which included 1065 employees which was used to assign staff schedule. In the third step, the demand forecasting occurred where staff demand generated using weekday-based forecasting models which were helped with staff schedule.

Then three different staff scheduling algorithms were used to generate staff roasters. First, we used MILP models which produces a roaster based on employee preference with optimization considerations by checking the staff availability, legal constraints and contract type. To achieve better scale further we used CP-SAT model which achieved similar schedule using constraint propagation. And finally, we were using GA model which was the most fit solution were repetitive development of staff schedule through evolution. All these models include numerical evaluation measures and final scores of weekly schedules which were used for comparison purposes.

6 Evaluation

The evaluation showed analysis of three given scheduling algorithms namely MILP, Genetic Algorithm (GA) and Constraint programming based on their performance in terms of visualizing distribution of workhour, results based on statistical conclusions and quantitative indicators. These terms were evaluated on both research and practical levels and results showed the fairness of model, viability of operations, following the labor laws and efficiency in optimization. The evaluation was done based on nine different indicators which include availability violations, total assigned shifts, breach of contract type, unmet demand, preference satisfaction, oversupply, rest day compliance. These terms were calculated with the help of statistical aggregation functions and got an opportunity to compare these three models. To understand how each model allocated hours among staff graphical plots such as histogram were used.

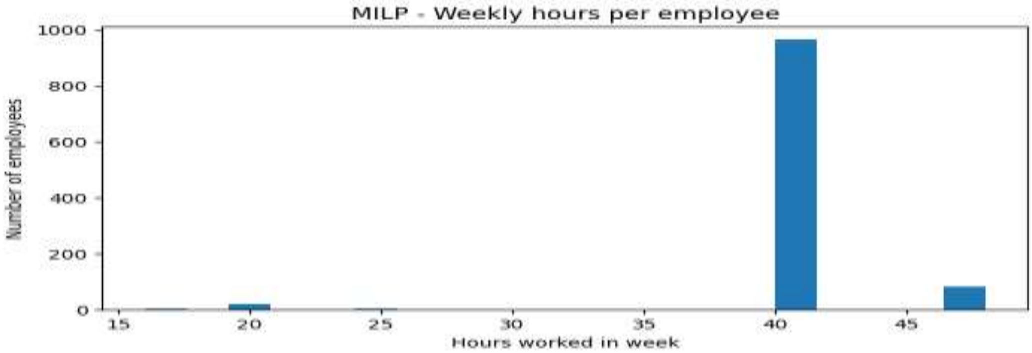
6.1 Experiment / Case Study 1 — MILP Scheduling

The MILP model was giving the highest assigned shifts, by showing its tendency to increase the object function. Although this gave result with 122 availability violations, over optimization at the cost of feasibility and 83 employees exceeding contract hours. However, this model achieved a good preference score, oversupplied of staff continuously showing the linear formulation prioritized preference score over efficiency of staffing. These results showed sensitivity to object weighting and difficulty in handling multi-domain staff scheduling with linear constraints. Practically manager would find this schedule unrealistic due to breach of legal compliance and overstaffing. The graph we can see as full time employees always exceeding the legal hours confirming imbalance of MILP model. Below is the output for the MILP model.

MILP assigned shifts: 7276

algorithm	employee_id	staff_name	staff_role	industry_type	contract_type
MILP	kavya_2	kavya	Assistant Manager	Restaurant	FT
MILP	kavya_2	kavya	Assistant	Restaurant	FT

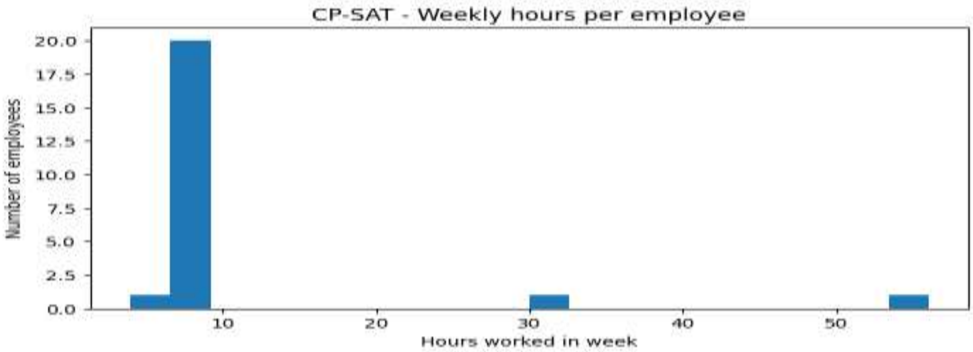
algorithm	employee_id	staff_name	staff_role	industry_type	contract_type
			Manager		
MILP	kavya_2	kavya	Assistant Manager	Restaurant	FT
MILP	kavya_2	kavya	Assistant Manager	Restaurant	FT



6.2 Experiment / Case Study 2 — CP-SAT Scheduling

The constraint programming model assigned only 31 shifts in total. This had shown highly conservative optimization behavior of model. If the shifts were fewer then it suggests strict satisfaction of constraint. Although model still has gone through 8 availability violations and 1 staff which exceeding 48 hours, indicated incomplete feasibility. This CP-SAT model also produced highest unmet demand, which indicates staff shortages or understaffing. Compared to MILP preference score of CP model aligned closely to it but preference satisfaction won't align as the assigned shifts were very less. The plot showed nearly zero distribution of weekly hours for staff scheduling. This shows that constraint propagation eliminates many solutions if it worked on large datasets, practically the schedule is unusable.
CP-SAT assigned shifts: 31

algorithm	employee_id	staff_name	staff_role	industry_type	contract_type
CP-SAT	S00319	S00319	ICU	Healthcare	FT
CP-SAT	S00337	S00337	Pediatrics	Healthcare	FT
CP-SAT	S00373	S00373	General Medicine	Healthcare	FT
CP-SAT	S00418	S00418	General Medicine	Healthcare	FT

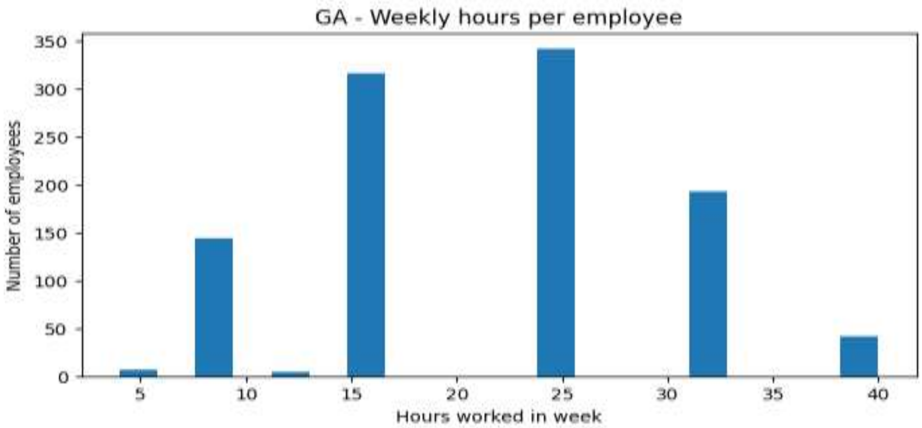


6.3 Experiment / Case Study 3 — Genetic Algorithm Scheduling

The genetic algorithm produces most realistic and balanced staff schedule compared to above two models with 2800 assigned shifts, no breach of contract hours and zero availability violations. Hower ever GA generated some oversupply and unmet demand, but these values are very much less that MILP and CP-SAT model. GA was having a high-performance score which shows its ability to handle constraints properly and effectively. The graph of hours distribution for GA models shows centered and smooth hours distribution, indicating uniform and fair shift allocation. GA achieved best tradeoff between optimization quality and feasibility. This model would produce a staff roaster which follow labor laws and staff availability. This shows the strength of heuristic searches in large datasets.

GA assigned shifts: 2799

algorithm	employee_id	staff_name	staff_role	industry_type	contract_type
GA	kavya_2	kavya	Assistant Manager	Restaurant	FT
GA	kavya_2	kavya	Assistant Manager	Restaurant	FT
GA	harini	harini	Barista	Restaurant	FT
GA	harini	harini	Barista	Restaurant	FT
GA	harini	harini	Barista	Restaurant	FT



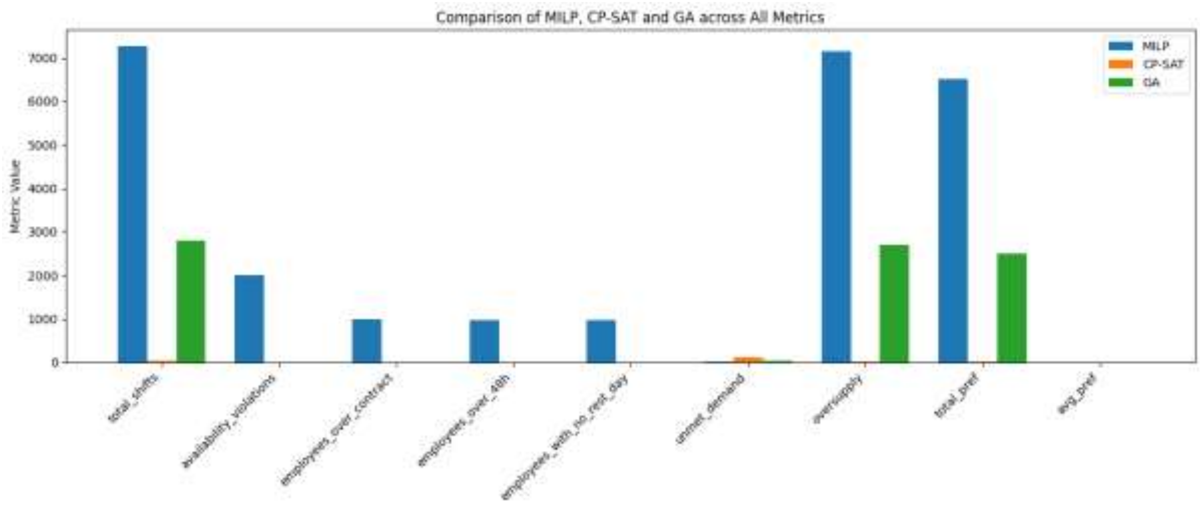
6.4 Experiment / Case Study 4 — Comparative Statistical Analysis

A three-model comparison was shown in this step. This model was compared based on standard deviation of weekly hours, mean preference score and counts of constraints violations. This indicates GA achieved a better optimality and feasibility balance. MILP high assigned shifts made goof preference but damaged constraint satisfaction which Constraint Programming understaffing and restrictive. This shown in result as GA is only model which produced real world schedules and handle large datasets due to its evolution search technique. MILP is good for small datasets. CP-SAT would be more useful in constraint propagation. +Overall, GA were correct for staff scheduling as an optimal approach in multi-industry sector dataset.

Below are the comparison plots for the models:

Optimization Models	**total_shifts**	**availability_violations**	**employees_over_contract**	**employees_over_48h**	**employees_with_no_rest_day**
MILP	7276.0	1996.0	983.0	972.0	972.0
CP-SAT	31.0	7.0	0.0	0.0	0.0
GA	2799.0	0.0	0.0	0.0	0.0

total_pref	**avg_pref**	**unmet_demand**	**oversupply**
6514.1	0.895286	12.0	7148.0
27.9	0.900000	121.0	12.0
2505.8	0.895248	36.0	2695.0



6.5 Discussion

The above comparison revealed differences in how MILP, GA and CP handle large scale multi domain staff scheduling. MILP assigned highest shift but gone through feasibility issues, while CP model assigned very few shifts that gave understaffing. GA gave a realistic and balanced staff schedule showing adaptability to difficult constraints. Although the model still has limitations, it depends on synthetic availability and simplified demand prediction. Improvements could include working with more advanced demand forecasting models such as TFT, using hybrid MILP-GA methods for performance enhancing or using reinforcement learning agent to check the schedules. When compared to existing research, it confirms past literature shown that heuristics approaches outperform solvers in multi domain scheduling problems.

7 Conclusion and Future Work

This study examined three optimization methods, namely, MILP, CP-SAT and Genetic Algorithms to solve automated staff scheduling in a restaurant sector, a retail sector, and a healthcare sector. The research was able to achieve its goal of creating a single framework that can generate compliant, equitable and demand responsive weekly rosters. The comparative analysis showed that GA provided schedules that were most balanced and legal, MILP made the best in terms of meeting staffing demand, and CP-SAT made high preference optimization but least reliable on strict constraints. Overall, the results indicate that Genetic-based optimization offers the most scalable and sound approach to workforce planning in multi-industry companies.

Future studies may combine the concept of real-time scheduling, in which last-minute cancellations or changes in demand may cause a re-optimization process. Extricate weekday-averaging may be substituted with a deep learning model that improves the quality of demand forecasting. It may also be possible to consider a hybrid optimization engine with CP-SAT constraint handling and preference learning of GA. The framework should also be extended to accommodate multi-shift days, hierarchies, modeling fatigue in employees and scheduling using reinforcement learning agents to make it more realistic. Lastly, the solution, applied as a cloud-based scheduling solution, may assist with commercial acceptance in big businesses.

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