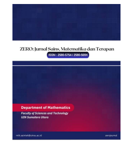
Zero : Jurnal Sains, Matematika, dan Terapan
E-ISSN : 2580-5754; P-ISSN : 2580-569X
Volume 10, Number 2, 2026
DOI: 10.30829/zero.v10i2.29388
Page: 588-601



Dual-Fairness Nurse Scheduling via the Double Direct Progressive Filling Algorithm under Qualification and Contract Constraints

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Article Info

Article history:

Accepted: 10 July 2026

Keywords:

DDPFA;
Fairness;
Hybrid Heuristic;
Nurse Scheduling Problem;
Optimization.

ABSTRACT

Nurse scheduling requires balancing workload distribution while satisfying qualification and employment contract constraints. This study implements a hybrid scheduling framework integrating Goal Programming (GP), the Double Direct Progressive Filling Algorithm (DDPFA), and the CP-SAT solver to generate feasible nurse schedules under actual and workforce-reduction scenarios in inpatient and emergency departments. Performance is evaluated using four indicators: inter-shift fairness, inter-nurse fairness, soft-constraint compliance, and computation time. The results show that the proposed approach achieves lower standard deviation values (0.15–0.42), satisfies all soft constraints, and generates feasible schedules in under 3 seconds. Compared with the evaluated manual scheduling and goal programming approaches, the framework produced more balanced workload allocation across shifts and nurses under the evaluated scenarios. These findings suggest that the proposed framework may provide a practical approach for fairness-oriented and cost-aware workforce planning under the evaluated hospital conditions.

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1. INTRODUCTION

The Nurse Scheduling Problem (NSP) is a widely studied combinatorial optimization problem in healthcare operations [1][2][3]. Hospitals operate continuously and require schedules that maintain adequate shift coverage, balanced workloads, and compliance with staffing regulations [4][5]. Inadequate scheduling may lead to nurse fatigue, decreased job satisfaction, and reduced quality of patient care [6][7]. These challenges have become increasingly critical due to workforce shortages, rising service demand, and operational cost pressures in healthcare systems.

In practice, NSP becomes more complex because nurses differ in qualifications, experience, and employment contracts, all of which must be aligned with operational requirements and regulatory policies [8][9][10][11]. Real-world scheduling practices further demonstrate the difficulty of generating feasible schedules under multiple operational and contractual constraints [12][13].

Various optimization approaches, including exact methods and goal programming, have been applied to NSP [14]. However, their computational performance often deteriorates as problem size increases, and many existing models do not explicitly ensure balanced workload distribution across shifts and among nurses [15][16][17][18]. To improve computational time and solution quality, heuristic and metaheuristic approaches such as simulated annealing and variable neighborhood search have been widely explored [19][20][21][22]. In addition, data-driven optimization techniques have also been applied in healthcare scheduling [23][24][25].

Among these approaches, the Double Direct Progressive Filling Algorithm (DDPFA) has been introduced as a fairness-based method that applies max–min and min–max principles to achieve balanced workload allocation [26][27][28]. These fairness principles are closely related to broader resource allocation models in optimization theory [29][30]. However, previous DDPFA-related studies mainly focused on workload allocation and have not fully integrated nurse qualification constraints, employment contract requirements, and operational scheduling complexity within a unified nurse scheduling framework [31][32].

In addition, existing studies have rarely combined dual-fairness evaluation, operational feasibility, and cost-efficiency considerations within the same scheduling model. Comprehensive evaluation using multiple indicators is particularly important in current healthcare environments characterized by staffing shortages, increasing service demand, and financial constraints [33][34].

To address these gaps, this study presents a dual-fairness nurse scheduling framework that integrates nurse qualification requirements, employment-contract constraints, and fairness-based allocation within a unified scheduling model. The framework is evaluated using four performance indicators, namely inter-shift fairness, inter-nurse fairness, soft-constraint compliance, and computation time, under both actual and workforce-reduction scenarios. In addition, workforce-reduction scenarios are used to examine the potential cost-efficiency of the proposed scheduling framework under the evaluated operational conditions. Rather than introducing a new optimization algorithm or claiming superiority over existing heuristic and metaheuristic approaches, this study focuses on demonstrating the practical integration of the DDPFA fairness mechanism with nurse qualification requirements, employment-contract constraints, and CP-SAT-based feasibility enforcement for hospital workforce scheduling. The main contributions of this study are: (1) integrating the DDPFA fairness mechanism with nurse qualification requirements, employment-contract constraints, and operational scheduling rules within a unified nurse scheduling framework, (2) evaluating workload fairness at both the inter-shift and inter-nurse levels within a unified scheduling framework, (3) evaluating workforce-reduction scenarios to assess whether cost-efficiency objectives can be achieved without substantially reducing schedule quality, and (4) providing a comprehensive assessment of scheduling performance through fairness, feasibility, computational tractability, and cost-efficiency analysis.

2. RESEARCH METHOD

2.1 Research Design

This study employs a computational quantitative approach to solve the Nurse Scheduling Problem (NSP) through an integrated optimization framework. The approach combines mathematical modeling, fairness-guided allocation, and constraint-based feasibility enforcement to evaluate scheduling performance using quantitative indicators, including fairness, soft-constraint compliance, and computation time. In this study, the term hybrid heuristic refers to the integration of three components: (1) Goal Programming (GP) for model formulation and constraint definition, (2) the Double Direct Progressive Filling Algorithm (DDPFA) as a fairness-driven allocation mechanism, and (3) a constraint programming solver (CP-SAT from OR-Tools) for enforcing feasibility. GP defines the optimization structure, DDPFA iteratively adjusts allocation bounds to achieve fairness, and CP-SAT ensures that all hard constraints remain satisfied throughout the solution process.

This study extends the DDPFA introduced by Obaid [26] through operational adaptation within a nurse scheduling context. The framework inherits the fairness mechanism based on max–min and min–max allocation principles while integrating nurse qualification constraints, employment-contract requirements, and operational scheduling rules into a unified dual-fairness scheduling framework. The framework applies a two-phase structure in which Phase 1 generates a feasible baseline solution satisfying all hard constraints, whereas Phase 2 improves workload distribution while preserving feasibility. In addition, the framework is evaluated under both actual and workforce-reduction scenarios using four complementary performance dimensions: inter-shift fairness, inter-nurse fairness, soft-constraint compliance, and computation time. The soft-constraint weights were determined based on operational priorities and expert judgment provided by nursing management. The overall scheduling procedure is further illustrated through the algorithmic flow presented in the subsequent section. Accordingly, the proposed framework extends the application of DDPFA to nurse scheduling rather than introducing a new optimization algorithm. Compared with the original DDPFA framework, it additionally incorporates nurse qualification requirements, employment-contract constraints, workforce-reduction scenario evaluation, and cost-efficiency assessment within a unified nurse scheduling framework.

2.2 Data Source and Collection

The research data were collected through face-to-face interviews with nursing management at Jakarta Cempaka Putih Islamic Hospital during January 2025. The data included the number of nurses, their qualifications, employment contract terms, and operational requirements in the Inpatient Care and Emergency Department (ED). The Inpatient Care unit had 24 nurses, while the ED had 30. Nurses were classified into three categories based on education, experience, and employment status, with parameters aligned with hospital regulations.

To ensure data reliability, interview results were cross-checked with official hospital documents, including employment contracts, staffing policies, and historical scheduling records. This validation process supports consistency between reported practices and actual operational conditions. The model was applied to a 24-hour service system with three shifts: morning (07:00–14:00), afternoon (14:00–21:00), and night (21:00–07:00), with one day off. Operational rules include one shift per day, a maximum of two consecutive identical shifts, mandatory rest after night shifts, and a maximum of six consecutive working days. Total working hours are also limited within a scheduling period, and each shift must satisfy minimum qualification requirements.

This study is designed as a controlled operational case study based on a single-institution, single-period dataset rather than a universally generalizable benchmark. The data reflect operational conditions in January 2025 and do not account for seasonal patterns, long-term workload variations, or institutional differences across hospitals. Furthermore, the model is developed under deterministic assumptions, in which nurse availability and service demand are treated as fixed conditions, while absenteeism, emergency demand surges, and stochastic uncertainty are not explicitly modeled.

Fairness is evaluated using standard deviation as the primary indicator of workload distribution. This metric is selected to provide a clear and interpretable measure of workload dispersion across nurses and shifts. Although alternative metrics such as the Gini coefficient or the max–min ratio could provide additional distributional insights, they are not included in this study and remain directions for future research. In addition, this study focuses on comparative evaluation under fixed experimental settings, and no statistical significance testing, stochastic validation, or robustness analysis is conducted. These limitations should be considered when interpreting the results, particularly regarding generalizability and real-world deployment.

2.3 Model Formulation

The model formulation in this study is derived from a goal programming framework, in which scheduling objectives and constraints are represented as mathematical goals and deviations. However, the formulated model is solved using the Double Direct Progressive Filling Algorithm (DDPFA) integrated with the CP-SAT solver rather than through conventional goal-programming optimization procedures.

The model uses the following sets: I is the set of nurses, J is the set of days in the scheduling period, W is the set of nurse qualifications, and $S = \{p, s, m, l\}$ represents the shift types: morning, afternoon, night, and day off. The indices $i \in I, j \in J, k \in W$ denote a nurse, a day, and a qualification, respectively. Model parameters include m as the number of nurses in a specific unit, n as the number of scheduling days (31 days), A^{tot} as the total number of hours worked by nurses during a given period, ω_t as the weight of each soft constraint or the t-th goal, and σ_k as the minimum number of nurses with a qualification k for each shift. The soft-constraint weights (3, 2, 1, 4, 5) were determined based on the relative importance of operational preferences observed in the hospital setting and informed by the head nurse's expert judgment. The weighting scheme was established directly through expert consultation with nursing management rather than through a formal multi-criteria weighting method such as AHP or Delphi. To improve transparency and reproducibility, Table 1 summarizes the operational rationale underlying the selected weighting scheme.

Table 1. Operational Rationale for Soft-Constraint Weights

Soft Constraint	Weight	Operational Rationale
Maximum two consecutive night shifts	3	To reduce nurse fatigue and support staff well-being.
Avoidance of off–on–off scheduling patterns	2	To improve schedule continuity and nurse satisfaction.
A maximum of eight night shifts per month	1	Considered more flexible operationally and less disruptive than other scheduling preferences.
Monthly working-hour target (±3 hours)	4	To support compliance with contractual working-hour requirements and workload regulation.
Minimum distribution of morning, afternoon, and night shifts	5	To maintain workload balance, fairness, and staffing stability across shift types.

The assigned weights reflect the relative priority of each soft constraint within the evaluated hospital setting and were established through consultation with nursing management. The weighting scheme is intended to represent practical scheduling preferences rather than mathematically optimized parameters and was not derived through formal optimization procedures, multi-criteria weighting methods, or sensitivity analysis. Therefore, the selected weights should be interpreted as a modeling assumption within the evaluated operational setting. Although the chosen values reflect local scheduling priorities, alternative weighting conFigureurations may produce different scheduling outcomes and warrant further investigation in future studies.

In addition, operational parameters were used that include F as the number of days off for each nurse, G as the maximum number of consecutive workdays, H as the maximum number of consecutive shifts of the same type, $Q, U,$ and V respectively, as the maximum number of morning, afternoon, and night shifts, B as the maximum number of consecutive night shifts, and δ, γ, μ respectively as the minimum number of morning, afternoon, and night shifts in a given period. The nurse-assignment decision is represented by a binary variable indicating whether nurse *i* is assigned to shift *s* on day *j*, defined as follows:

$$p_{i,j,k} = \begin{cases} 1, & \text{if nurse } i \text{ with qualification } k \text{ is assigned the morning shift on day } j, \\ 0, & \text{if otherwise.} \end{cases} \tag{1}$$

$$s_{i,j,k} = \begin{cases} 1, & \text{if nurse } i \text{ with qualification } k \text{ is assigned the afternoon shift on day } j, \\ 0, & \text{if otherwise.} \end{cases} \tag{2}$$

$$m_{i,j,k} = \begin{cases} 1, & \text{if nurse } i \text{ with qualification } k \text{ is assigned the night shift on day } j, \\ 0, & \text{if otherwise.} \end{cases} \tag{3}$$

$$l_{i,j,k} = \begin{cases} 1, & \text{if nurse } i \text{ with qualification } k \text{ has a day off on day } j, \\ 0, & \text{if otherwise.} \end{cases} \tag{4}$$

These four variables satisfy the exclusivity condition, meaning each nurse can be assigned only one type of task per day. The deviation variable is used in the goal programming framework to measure deviations from the established targets [5][14]. The variables $d^+_{t,i,k}$ and $d^-_{t,i,k}$ represent, respectively, the excess and shortfall in the achievement of the t-th goal by the nurse i with qualification k. For constraints that depend on a specific day, the variables $d^+_{t,i,j,k}$ and $d^-_{t,i,j,k}$ are used to denote the deviation from the target for the nurse i on day j. All deviation variables are non-negative. The goal programming objective function is then formulated as the minimization of the total weighted deviation:

$$\begin{aligned} \min Z = {} & \omega_1 \sum_{i=1}^{i_3} \sum_{j=1}^{n} \sum_{k=1}^{3} d^+_{1,i,j,k} + \omega_2 \sum_{i=1}^{i_3} \sum_{j=1}^{n} \sum_{k=1}^{3} d^+_{2,i,j,k} + \omega_3 \sum_{i=1}^{i_3} \sum_{k=1}^{3} d^+_{3,i,k} \\ & + \omega_4 \sum_{i=1}^{i_3} \sum_{k=1}^{3} d^+_{4,i,k} + \omega_5 \sum_{i=1}^{i_3} \sum_{k=1}^{3} d^-_{5,i,k} + \omega_5 \sum_{i=1}^{i_3} \sum_{k=1}^{3} d^-_{6,i,k} + \omega_5 \sum_{i=1}^{i_3} \sum_{k=1}^{3} d^-_{7,i,k} \end{aligned} \tag{5}$$

The hard constraints are as follows:

$$\textstyle\sum_{i \in I_k} p_{i,j,k} \geq \sigma_k, \sum_{i \in I_k} s_{i,j,k} \geq \sigma_k, \sum_{i \in I_k} m_{i,j,k} \geq \sigma_k, \forall j \in J \tag{6}$$

$$p_{i,j,k} + s_{i,j,k} + m_{i,j,k} + l_{i,j,k} = 1, \forall i \in I, \forall j \in J, \forall k \in W \tag{7}$$

$$\textstyle\sum_{k=1}^{3} (m_{i,j,k} + p_{i,j+1,k}) \leq 1, \forall i \in I, \forall j \in J \tag{8}$$

$$\textstyle\sum_{k=1}^{3} (m_{i,j,k} + s_{i,j+1,k}) \leq 1, \forall i \in I,\ j = 1, 2, \dots, n-1 \tag{9}$$

$$\textstyle\sum_{j=1}^{n} \sum_{k=1}^{3} l_{i,j,k} = F, \forall i \in I \tag{10}$$

$$\textstyle\sum_{k=1}^{3} (l_{i,j,k} + l_{i,j+1,k} + \cdots + l_{i,j+G,k}) \geq 1, \forall i \in I,\ j = 1, 2, \dots, n-G \tag{11}$$

$$\begin{gathered} \textstyle\sum_{k=1}^{3} (p_{i,j,k} + p_{i,j+1,k} + \cdots + p_{i,j+H,k}) \leq H, \sum_{k=1}^{3} (s_{i,j,k} + s_{i,j+1,k} + \dots + s_{i,j+H,k}) \leq H, \\ \textstyle\sum_{k=1}^{3} (m_{i,j,k} + m_{i,j+1,k} + \cdots + m_{i,j+H,k}) \leq H, \forall i \in I,\ j = 1, 2, \dots, n-H \end{gathered} \tag{12}$$

$$\textstyle\sum_{j=1}^{n} \sum_{k=1}^{3} p_{i,j,k} \leq Q, \forall i \in I \tag{13}$$

$$\textstyle\sum_{j=1}^{n} \sum_{k=1}^{3} s_{i,j,k} \leq U, \forall i \in I \tag{14}$$

With the following conditions: Equation (6) ensuring that the minimum number of qualified nurses staffs each shift on every day; Equation (7) limiting each nurse to only one shift per day; Equation (8) and Equation (9) prohibiting the assignment of morning or afternoon shifts after a nurse has worked a night shift the previous day to ensure adequate rest time; Equation (10) ensuring that every nurse receives the number of days off specified in their contract within a single scheduling period, Equation (11) limiting the number of consecutive workdays without days off, Equation (12) limiting the number of consecutive shifts of the same type, Equation (13) and Equation (14) setting a maximum limit on morning and afternoon shifts within a single scheduling period. Additionally, the following constraints apply:

$$m_{i,j,k} + m_{i,j+1,k} + \cdots + m_{i,j+B,k} \leq B, \forall i \in I, \forall k \in W,\ j = 1,2, \dots, n-B \tag{15}$$

$$l_{i,j,k} + p_{i,j+1,k} + s_{i,j+1,k} + m_{i,j+1,k} + l_{i,j+2,k} \leq 2, \forall i \in I, \forall k \in W,\ j = 1,2, \dots, n-2 \tag{16}$$

$$\textstyle\sum_{j=1}^{n} m_{i,j,k} \leq V, \forall i \in I, \forall k \in W \tag{17}$$

$$7 \textstyle\sum_{j=1}^{n} p_{i,j,k} + 7 \sum_{j=1}^{n} s_{i,j,k} + 10 \sum_{j=1}^{n} m_{i,j,k} \leq A^{tot}, \forall i \in I, \forall k \in W \tag{18}$$

$$\textstyle\sum_{j=1}^{n} p_{i,j,k} \geq \delta, \sum_{j=1}^{n} s_{i,j,k} \geq \gamma, \sum_{j=1}^{n} m_{i,j,k} \geq \mu, \forall i \in I, \forall k \in W \tag{19}$$

Specifically, Equation (15) limits the number of consecutive night shifts a nurse may work before taking a break, Equation (16) prevents an "off–on–off" scheduling pattern, Equation (17) limits the total number of night shifts in a single period, Equation (18) regulates the total working hours, and Equation (19) ensures that each nurse receives a minimum number of morning, afternoon, and night shifts in a single period to maintain a balanced distribution of shift types. This model assumes that each nurse can work only one shift per day and that all operational parameters are deterministic during the scheduling period.

2.4 Double Direct Progressive Filling Algorithm (DDPFA)

The Double Direct Progressive Filling Algorithm (DDPFA) is implemented in this study as a heuristic allocation mechanism that guides the progressive assignment of nurses based on dual-fairness principles. The algorithm operates at the decision-making level by iteratively adjusting allocation bounds, while the feasibility of the resulting schedule is ensured through the underlying constraint model. In this context, DDPFA serves as a constructive heuristic for generating balanced scheduling decisions, rather than relying on a purely exact optimization solver. The implementation of DDPFA is integrated with the constraint-based formulation to ensure that all scheduling decisions remain feasible throughout the iterative process. The algorithm progressively adjusts allocation parameters without violating the predefined constraints, allowing the model to maintain both feasibility and fairness simultaneously.

The method used in this study is an adaptation of the Double Direct Progressive Filling Algorithm (DDPFA) introduced by Obaid [26] for nurse scheduling, based on the principles of double max–min fairness: equitable allocation of nurses across shifts and equitable distribution of workloads among nurses. DDPFA was developed based on the progressive filling concept, which operates iteratively by increasing the lower bound of allocation and controlling the upper bound of workload until a stable and fair distribution is achieved [27][28].

In this study, the basic framework of DDPFA is retained and applied to a more complex context by integrating nurse qualification constraints, employment contracts, and hospital operational rules into the scheduling process. In addition to achieving fairness, the approach also incorporates soft-constraint-based evaluation and computational time considerations to produce a more comprehensive and practical solution. This allows the model to generate schedules that satisfy all constraints while maintaining efficient computational performance compared to exact methods [27][28][34].

The DDPFA algorithm is implemented in two main phases. In the first phase, the focus is on ensuring a fair distribution of nurses across shifts (inter-shift fairness). In contrast, the second phase aims to balance workload distribution among nurses (inter-individual fairness). The iteration index η It is used in the first phase to control fairness across shifts. In contrast, the index ρ is used in the second phase to regulate the distribution of workload among nurses. The decision variable $\alpha_\eta \in R^+$ represents the lower bound of the minimum number of. In contrast, per shift at iteration η with the optimal value α_η^*, while $\beta_\rho \in R^+$ denotes the upper bound on the maximum number of shifts per nurse at iteration ρ with the optimal value of the parameter β_ρ^*. These parameters are updated iteratively until a stable and feasible solution is obtained.

Phase 1 (Fairness across shifts)

$$\sum_{i=1}^{m}\sum_{k=1}^{3} p_{i,j,k} \geq \alpha_\eta, \sum_{i=1}^{m}\sum_{k=1}^{3} s_{i,j,k} \geq \alpha_\eta, \sum_{i=1}^{m}\sum_{k=1}^{3} m_{i,j,k} \geq \alpha_\eta, \forall j \in J \tag{20}$$

$$\sum_{i=1}^{m}\sum_{k=1}^{3} p_{i,j,k} \leq \alpha_\eta^* + 1, \sum_{i=1}^{m}\sum_{k=1}^{3} s_{i,j,k} \leq \alpha_\eta^* + 1, \sum_{i=1}^{m}\sum_{k=1}^{3} m_{i,j,k} \leq \alpha_\eta^* + 1, \forall j \in J. \tag{21}$$

$$\max Z_1 = \alpha_\eta \tag{22}$$

Phase 2 (Fairness among nurses)

$$\sum_{i=1}^{m}\sum_{k=1}^{3} p_{i,j,k} \geq \alpha_\eta^*, \sum_{i=1}^{m}\sum_{k=1}^{3} s_{i,j,k} \geq \alpha_\eta^*, \sum_{i=1}^{m}\sum_{k=1}^{3} m_{i,j,k} \geq \alpha_\eta^*, \forall j \in J \tag{23}$$

$$\sum_{j=1}^{n}\sum_{k=1}^{3} (p_{i,j,k} + s_{i,j,k} + m_{i,j,k}) \leq \beta_\rho, \forall i \in I \tag{24}$$

$$\sum_{j=1}^{n}\sum_{k=1}^{3} (p_{i,j,k} + s_{i,j,k} + m_{i,j,k}) \leq \beta_\rho^*, \forall i \in I \tag{25}$$

$$\min Z_2 = \beta_\rho \tag{26}$$

Specifically, in Phase 1, Equation (20) specifies the minimum constraint on the number of nurses per shift, Equation (21) defines a blocking constraint to prevent over-scheduling of already-filled shifts, and Equation (22) represents the objective function that maximizes the distribution of nurses across shifts. In Phase 2, Equation (23) constrains Phase 2 to preserve the allocation results obtained in Phase 1, Equation (24) imposes a maximum constraint on the number of shifts per nurse, Equation (25) defines a blocking constraint on nurses' workloads, and Equation (26) represents the objective function that minimizes the maximum workload per nurse. The final process is the evaluation of soft constraints:

$$S^* = \arg\min_{S \in \psi} \left(\sum_{t=1}^{5} \omega_t P_t(S) \right) \tag{27}$$

A final evaluation is performed using Equation (27) for each candidate solution based on the total soft constraint penalty, where $P_t(S)$ denotes the t-th penalty and ω_t the corresponding weight. The set ψ comprises all feasible schedules that satisfy both Phase 1 and Phase 2. The final solution S^* is selected as the schedule with the minimum total penalty from that set.

The interaction between Phase 1 and Phase 2 is designed to preserve feasibility throughout the solution process. The solution obtained in Phase 1 establishes a feasible baseline that satisfies all hard constraints, particularly those related to shift coverage and qualification requirements. In Phase 2, workload distribution among nurses is adjusted within the feasible solution space defined in Phase 1, keeping all hard constraints fixed while modifying allocation bounds through controlled parameter updates. Therefore, Phase 2 does not alter feasibility but redistributes assignments within the feasible region. This is further supported by the absence of hard-constraint violations in all generated schedules during the evaluation phase. The detailed algorithmic flow of the DDPFA-based scheduling framework is illustrated in Figure. 1.

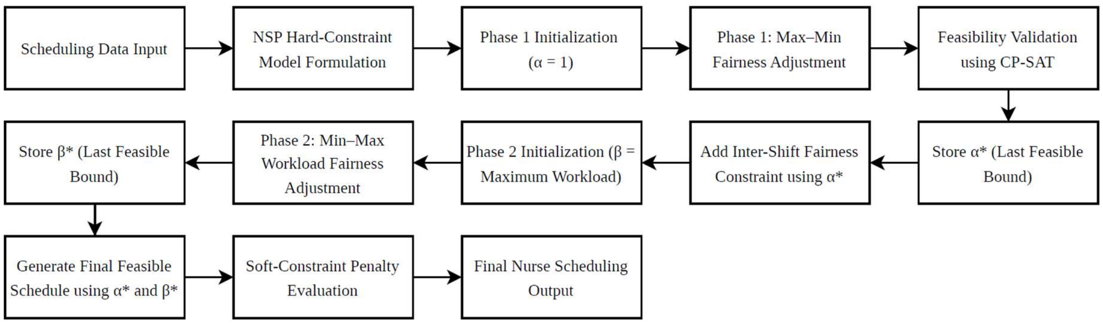

Figure 1. Algorithmic flow of the DDPFA-based nurse scheduling framework.

The flowchart summarizes the iterative interaction between DDPFA and the CP-SAT solver during fairness adjustment, feasibility validation, and final schedule generation. The framework is implemented in Python using a constraint-based solver (CP-SAT) to ensure that all model constraints are satisfied. In this framework, DDPFA does not operate as a standalone constructive heuristic. Instead, it interacts iteratively with the CP-SAT solver, where each allocation adjustment is validated to ensure constraint satisfaction. DDPFA guides the allocation process toward a fair distribution, while the solver enforces feasibility throughout the solution process. This integration enables the generation of feasible schedules while supporting fairness-oriented allocation. This study does not include an ablation analysis to isolate the contribution of individual algorithmic components. Consequently, the individual contribution of each component (GP formulation, DDPFA allocation mechanism, and CP-SAT feasibility enforcement) cannot be isolated within the current experimental design, and a formal ablation study remains an important direction for future research. However, the framework is evaluated against manual scheduling and goal programming, providing a practical assessment within the operational context considered in this study.

3. RESULT AND ANALYSIS

The performance comparison in this study is based on descriptive evaluation across multiple indicators, including fairness, soft-constraint satisfaction, and computation time. Formal statistical significance testing is not conducted because the analysis focuses on comparative performance under identical experimental conditions. Therefore, the results are interpreted based on relative differences between methods rather than inferential statistical measures. In addition to standard deviation, descriptive measures such as minimum–maximum ranges and distributional analysis are used to provide a broader interpretation of workload balance and to avoid masking potential disparities. Because the proposed framework operates under deterministic settings and fixed solver conFigureurations, repeated executions under identical conditions produce identical scheduling outcomes. Consequently, variability analysis, confidence intervals, and inferential statistical testing are not applicable within the current experimental design. Future studies may incorporate stochastic demand conditions, parameter perturbations, or repeated experimental runs to further assess robustness under varying operational conditions.

3.1 Feasibility and Hard Constraint Satisfaction

An initial evaluation was conducted to assess compliance with hard constraints in manual scheduling, Goal Programming (GP), and the Double Direct Progressive Filling Algorithm (DDPFA) in the Inpatient Care and the Emergency Department. Hard constraints in this study refer to the model formulation, namely Equation (6)–Equation (14), which include Equation (6) ensuring that the minimum number of nurses staffs each shift on every day according to their qualifications, Equation (7) limiting each nurse to only one shift per day, Equation (8) and Equation (9) prohibiting the assignment of morning or afternoon shifts after a nurse has worked a night shift the previous day to ensure adequate rest time, Equation (10) ensuring that each nurse receives the number of days off specified in their contract within a single scheduling period, Equation (11) limiting the number of consecutive workdays without days off, Equation (12) limiting the number of consecutive shifts of the same type, Equation (13) and Equation (14) setting the maximum limits for morning and afternoon shifts within a single scheduling period.

Table 2. Comparison of Hard Constraint Fulfillment for Manual, GP, and DDPFA Methods

Methods	Hard Constraints								
	6	7	8	9	10	11	12	13	14
Manual	✗	✓	✓	✓	✗	✗	✗	✗	✗
GP	✓	✓	✓	✓	✓	✓	✓	✓	✓
DDPFA	✓	✓	✓	✓	✓	✓	✓	✓	✓

Table 2 shows that the manual method has not satisfied all hard constraints, particularly those related to qualification requirements, holidays, limits on consecutive workdays, and shift distribution. These violations indicate that the manual approach is not systematic enough to accommodate the complexity of interacting operational rules. In contrast, GP and DDPFA successfully met all major constraints, indicating that both optimization methods can produce mathematically feasible solutions. The ability of GP and DDPFA to satisfy all hard constraints indicates that optimization-based approaches can generate feasible schedules while accommodating interdependencies among constraints under the evaluated conditions. This is important because solution feasibility is a primary prerequisite before conducting further evaluations of fairness, soft constraints, and computation time. Thus, these results indicate that optimization methods can support rule compliance and the generation of operationally valid schedules under the evaluated condition.

3.2 Fairness Performance Analysis

The performance comparison between DDPFA and Goal Programming (GP) was analyzed using multiple descriptive fairness indicators, including standard deviation, workload distribution patterns, and minimum–maximum allocation ranges. Among these indicators, standard deviation is used to quantify allocation variability, with lower values indicating a more even distribution. Figureure 2 compares these two indicators in the Inpatient Care and the Emergency Department for each scenario.

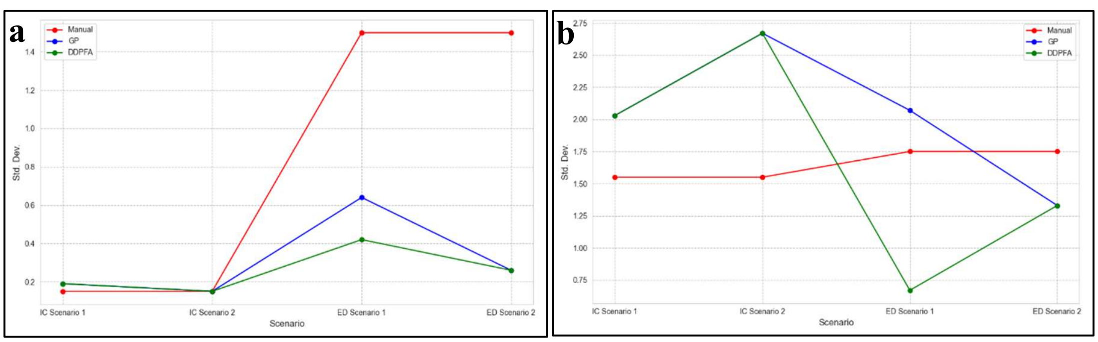

Figure. 2. Standard Deviation of (a) Inter-Shift Fairness and (b) Inter-Nurse Workload Fairness

Figure. 2(a) shows the standard deviation of inter-shift fairness. In the Inpatient Care unit, the standard deviation indicates a relatively similar level of stability between the GP and DDPFA methods, with values of 0.19 (Scenario 1) and 0.15 (Scenario 2), respectively. In contrast, the manual method shows larger and less consistent variations in standard deviation across units. The difference in performance is more evident in the Emergency Department (ED), where DDPFA has a lower standard deviation (0.42) than GP (0.64). This suggests that DDPFA provides a more balanced distribution across shifts in more dynamic operational environments such as the Emergency Department. Conceptually, the progressive filling mechanism in DDPFA is intended to support a more balanced distribution through a max–min fairness approach, which may contribute to lower inter-shift disparities.

Figure. 2(b) shows the standard deviation of inter-nurse workload fairness, where the differences between methods were more pronounced. In the Inpatient Care unit, both GP and DDPFA yielded the same standard deviation values, namely 2.03 (Scenario 1) and 2.67 (Scenario 2), while more noticeable differences were observed in the Emergency Department. In the Emergency Department (ED), DDPFA had a lower standard deviation (0.67) than GP (2.07), indicating a more even distribution of workload among nurses. These results suggest that DDPFA maintains balance across shifts while supporting a more even distribution of workload among nurses. The manual method, on the other hand, showed moderate stability in workload distribution, likely due to its simpler scheduling pattern that did not fully account for complex constraints.

However, it did not maintain consistency across both fairness indicators simultaneously. Although fairness in workload distribution among nurses (inter-nurse fairness) is an important indicator, achieving balanced individual workloads is relatively common in scheduling models that incorporate workload constraints. Therefore, it is also essential to examine fairness across shifts (inter-shift fairness), which reflects how evenly nurses are distributed among them. This aspect is more closely related to operational stability and the balance of shift coverage. The results indicate that DDPFA achieved balanced outcomes across both inter-nurse and inter-shift fairness measures under the evaluated scenarios, suggesting its suitability for handling multiple fairness objectives within a unified framework.

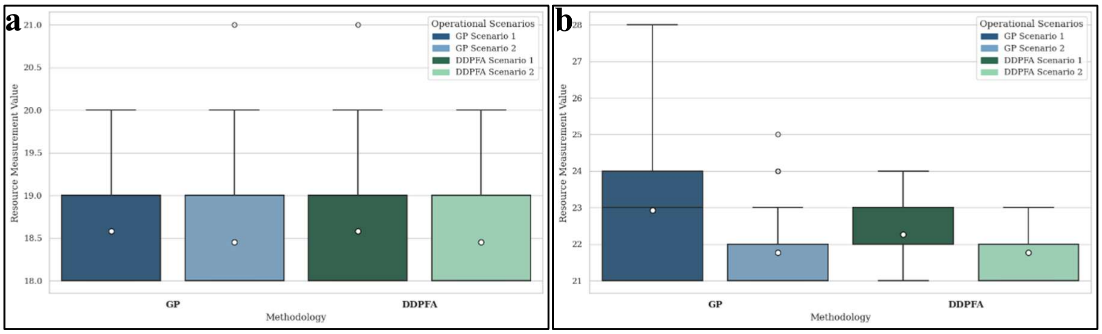

Figure. 3. Distribution of Inter-Shift Workload across Methods and Scenarios: (a) Inpatient Care and (b) Emergency Department

Figure. 3 shows the distribution of inter-shift workload across methods and scenarios. In Figure. 3(a), which represents the Inpatient Care unit, the workload distribution is highly consistent across all methods and scenarios. The interquartile ranges are narrow and the values are tightly clustered, indicating low variability in shift allocation. This suggests that nurse distribution across shifts is stable and well-balanced in this unit.

In Figure. 3(b), which represents the Emergency Department, a slightly wider spread is observed, reflecting more dynamic operational conditions. However, the distribution remains well-controlled, with no extreme outliers. Compared to GP, the DDPFA method exhibits a more compact distribution, indicating a more balanced allocation of nurses across shifts. These results complement the standard deviation analysis by providing additional insight into workload distribution patterns and allocation variability across shifts.

DDPFA exhibits stable performance across both fairness indicators, particularly in units with higher operational variability. To provide a clearer understanding of fairness across shifts beyond standard deviation and distributional analyses, this study examines the distribution of nurse assignments by shift using the minimum and maximum values. The results of this analysis for each method, unit, and scenario are presented in Table 3.

Table 3. Distribution of Nurses per Shift (Min–Max Range)

Method	Unit	Scenario	Min (Shifts)	Max (Shifts)	Range (Shifts)
DDPFA	IC	Actual & Efficiency	6	7	1
DDPFA	ED	Actual & Efficiency	7	8	1
GP	ED	Actual & Efficiency	7	10	3
Manual	ED	Actual	4	11	7

In addition to standard deviation, fairness across shifts is further evaluated using the minimum–maximum range of nurse assignments per shift, as presented in Table 3. This analysis reflects inter-shift fairness and allows comparison of how evenly nurses are distributed across shifts under different methods. A narrower range indicates a more even distribution and supports operational stability.

The results show that DDPFA consistently produces the narrowest range across all scenarios, indicating a more balanced allocation and reduced disparity in shift coverage. Compared to goal programming and manual scheduling, DDPFA reduces extreme differences in the number of nurses assigned to each shift, resulting in a more controlled and stable distribution. Overall, these results suggest that DDPFA provides a more balanced inter-shift distribution under the evaluated scenarios, particularly in environments with varying operational demands. This range-based analysis complements standard deviation by capturing potential extreme values in shift allocation, thereby providing a more comprehensive assessment of fairness distribution.

These results are consistent with Obaid (2024), who reported that DDPFA achieved max–min fairness and min–max fairness through a two-stage progressive filling mechanism. However, unlike that study, which focused on resource and workload allocation, this study extends DDPFA by integrating constraints on qualifications and employment contracts. It also evaluates the model's performance more comprehensively using fairness metrics, soft constraint satisfaction, and computational time. These findings should be interpreted within the scope of the evaluated scenarios. Although additional fairness indicators such as the Gini coefficient, Lorenz analysis, or max–min fairness indices could provide further distributional insights, this study focuses on standard deviation, distributional analysis, and range-based measures to maintain interpretability within the evaluated operational setting.

3.3 Soft Constraint Compliance

An evaluation of compliance with soft constraints, based on weighted penalty values, was conducted for the DDPFA method, Goal Programming (GP), and manual scheduling. The penalty weights reflect the relative operational importance of each soft constraint, as described in Table 1. This analysis aims to assess each method's consistency in maintaining compliance with soft constraints without compromising distribution stability. Figureure 4 presents a comparison of compliance levels in the Inpatient Care and the Emergency Department.

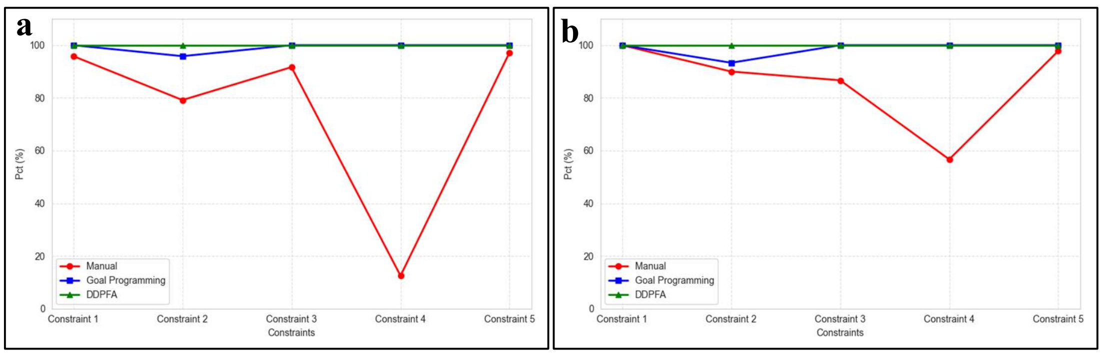

Figure. 4. Percentage of Soft Constraint Compliance in (a) Inpatient Care and (b) Emergency Department

Figure. 4(a) shows the level of compliance with soft constraints in the Inpatient Care unit. The DDPFA method achieved full (100%) satisfaction of all soft constraints, with no observed violations. This indicates that the method maintained solution consistency under the evaluated scheduling conditions. In contrast, GP shows a high compliance rate, averaging around 99.17%, but there are still violations of the off–on–off scheduling pattern constraint. The manual method shows a more variable compliance rate, particularly in the distribution of night shifts and scheduling patterns, and has not met the contract's total working-hour limits. These differences suggest that optimization approaches provide higher levels of soft-constraint compliance than manual scheduling under the evaluated conditions.

Figure. 4(b) shows that in the ED unit, DDPFA again achieved full compliance with all soft constraints, indicating high consistency under more dynamic operational conditions. GP maintained a relatively high compliance rate, averaging around 98.67%, but still exhibited minor deviations regarding scheduling pattern constraints. Meanwhile, the manual method exhibited greater instability, particularly in shift distribution and work patterns, and failed to meet the total working-hour limits required by regulations. These results indicate that DDPFA achieves high levels of soft-constraint compliance while maintaining solution stability in the evaluated higher-complexity environments.

The observed differences should also be interpreted in light of the weighting scheme adopted in the soft-constraint model. Higher weights were assigned to workload balance and contractual compliance, which are indirectly supported by the fairness-adjustment mechanism in DDPFA. Consequently, the fairness-oriented allocation process may contribute to lower violations in highly prioritized soft constraints under the evaluated scenarios.

Conceptually, the high level of soft-constraint compliance observed in DDPFA may be associated with the double-fairness mechanism that regulates allocation at both the shift and individual levels. A more balanced distribution can contribute to a more stable allocation pattern and may help reduce violations of soft constraints. This finding is also consistent with the fairness analysis results in the previous section, where more equitable distributions were associated with higher levels of soft-constraint compliance.

3.4 Computational Time

To evaluate computational time, the performance of Goal Programming (GP) and DDPFA was compared using computation time per unit and per scenario. Computation time is a key indicator of a model's feasibility, particularly in hospital scheduling systems that require fast, repetitive processes. Table 4 presents the results of the comparison of computation times for the two methods.

Table 4. Comparison of Computational Time Between Goal Programming and DDPFA

Unit	Goal Programming		DDPFA	
	Scenario 1 (seconds)	Scenario 2 (seconds)	Scenario 1 (seconds)	Scenario 2 (seconds)
Inpatient Care	146	229	2.26	19.12
Emergency Department	28.13	24.47	2.88	2.89

Table 4 shows the computation time required by each method across different units and scenarios. In the Inpatient Care unit, GP's computation time increased from 146 seconds to 229 seconds as scenario complexity increased, whereas DDPFA remained within a considerably lower range. A similar pattern is observed in the Emergency Department, where DDPFA maintained stable computation times below 3 seconds, while GP required longer processing times. These results indicate that the DDPFA-based implementation achieved lower computation times than GP under the evaluated computational settings, particularly in constraint-intensive scheduling scenarios. It should be noted that the observed computational time reflects the interaction between the DDPFA mechanism and the CP-SAT solver, rather than solely the algorithm's intrinsic efficiency. In addition, no sensitivity analysis on solver conFigureurations or hardware environments was conducted in this study. Therefore, the reported computation times should be interpreted as implementation-specific performance results under the evaluated computational settings. Sensitivity analysis and perturbation-based evaluation were not conducted in this study and remain important directions for future research to further assess the robustness of the proposed scheduling framework under varying operational conditions.

3.5 Managerial Insights

The results of this study suggest that the achieved cost efficiency was accompanied by favorable performance in terms of hard- and soft-constraint satisfaction, fairness, and computation time. The DDPFA-based scheduling framework supports a balance between operational efficiency and workload distribution and may serve as both a scheduling and decision-support tool for workforce planning. These findings highlight the practical relevance of fairness-driven scheduling for workforce planning and cost-efficiency evaluation in hospital operations.

From a managerial perspective, this approach supports improved workforce allocation and cost-efficiency decisions. By integrating fairness across shifts and among nurses, the model supports balanced staffing while maintaining scheduling feasibility. However, the findings are based on a single hospital and do not incorporate individual nurse preferences, which may affect generalizability and schedule acceptability. A cost-efficiency analysis was conducted under actual and workforce-reduction scenarios, with the results presented in Tables 5 and 6.

The cost-efficiency analysis is based on a simplified wage model in which all nurses are assumed to receive a fixed monthly salary of IDR 5,000,000. Overtime compensation is calculated at a standard rate of 1/173 of the monthly salary per hour, in accordance with common labor regulations. The cost-efficiency analysis focuses on direct labor costs, which consist of base salary expenditure and overtime compensation. The total monthly nurse cost is calculated as the sum of base salary expenditure and overtime compensation, as expressed in Equation (28).

$$TC = BS + OC \tag{28}$$

The base salary expenditure is calculated as:

$$BS = N \times S \tag{29}$$

The overtime compensation is calculated as:

$$OC = H_{OT} \times {}^{S}/_{173} \tag{30}$$

where:
TC = total monthly nurse cost;
BS = total base salary expenditure;
OC = total overtime compensation;
N = number of nurses;
S = monthly salary per nurse;
H_{OT} = total overtime hours.

Therefore, indirect operational costs, administrative costs, training costs, and other hospital expenditures are not included in the analysis. Under these assumptions, the base salary expenditure is obtained by multiplying the number of nurses by the assumed monthly salary, while overtime compensation is calculated based on the total overtime hours and the standard overtime rate of 1/173 of the monthly salary per hour. This simplified formulation is intended to provide a consistent basis for comparing cost-efficiency across scheduling scenarios. No sensitivity analysis on wage levels or overtime limits was conducted in this study. Therefore, the reported cost values should be interpreted as comparative operational estimates within the evaluated scenarios.

Furthermore, the cost model assumes a uniform monthly salary and standard overtime compensation and does not incorporate additional payroll components such as night-shift allowances, weekend or holiday premiums, or other institutional compensation policies. Consequently, the reported cost estimates should be interpreted as comparative estimates of direct labor costs under a simplified wage structure. Incorporating more detailed payroll components would provide a more comprehensive financial evaluation and represent an important direction for future research.

Table 5. Comparison of Total Nurse Cost in the Inpatient Care

Description	Actual Scenario	Efficiency Scenario
Number of nurses	24 nurses	22 nurses
Total base salary (IDR/month)	120,000,000	110,000,000
Overtime shifts per nurse	-	2 overtime shifts
Total overtime pay (IDR/month)	-	8,901,734
Total cost (IDR/month)	120,000,000	118,901,734

As shown in Table 5, the Inpatient Care unit experienced a reduction in total cost under the efficiency scenario. The number of nurses decreased from 24 to 22, reducing total monthly salary expenditure from IDR 120,000,000 to IDR 110,000,000. Although overtime shifts were introduced, leading to an additional cost of IDR 8,901,734, the total operational cost remained lower at IDR 118,901,734. This corresponds to an estimated cost reduction of approximately 0.92% relative to the actual scenario. These results suggest that the adjusted scheduling conFigureuration maintained scheduling feasibility while improving cost efficiency, indicating that optimized workforce allocation may contribute to improved cost efficiency under comparable operational conditions. The same cost assumptions and calculation framework are applied to the Emergency Department, as presented in Table 6.

Table 6. Comparison of Total Nurse Cost in the Emergency Department

Description	Actual Scenario	Efficiency Scenario
Number of nurses	30 nurses	27 nurses
Total base salary (IDR/month)	150,000,000	135,000,000
Overtime shifts per nurse	-	2 overtime shifts
Total overtime pay (IDR/month)	-	10,924,855
Total cost (IDR/month)	150,000,000	145,924,855

A similar pattern is observed in the Emergency Department, as presented in Table 6. Reducing the number of nurses from 30 to 27 decreased the total salary cost from IDR 150,000,000 to IDR 135,000,000 per month. Despite the addition of overtime incentives amounting to IDR 10,924,855, the total cost was reduced to IDR 145,924,855. This corresponds to an estimated cost reduction of approximately 2.72% relative to the actual scenario. This finding suggests that a controlled workforce reduction, when combined with optimized scheduling, may improve cost efficiency while maintaining scheduling feasibility under the evaluated scenarios.

The comparative evaluation in this study focuses on manual scheduling and goal programming (GP) as baseline approaches commonly applied in real-world hospital settings. While these methods provide a relevant operational reference, the benchmarking scope does not include advanced heuristic and metaheuristic approaches such as variable neighborhood search (VNS), genetic algorithms (GA), simulated annealing (SA), or adaptive large neighborhood search (ALNS), which are widely used in nurse scheduling literature. The DDPFA-based scheduling framework evaluated in this study is designed to support fairness-oriented allocation and practical interpretability within a constraint-based scheduling environment. However, because advanced metaheuristic approaches such as VNS, GA, SA, and ALNS are not included in the benchmarking process, no direct performance comparison can be made. Therefore, the findings should be interpreted as evidence of the practical applicability of fairness-driven scheduling rather than as a direct performance comparison against state-of-the-art metaheuristic optimization methods.

This study does not explicitly analyze the computational complexity of the proposed approach or its scalability to larger problem instances. The current implementation is evaluated on single-unit scheduling scenarios with a fixed planning horizon. Although the results demonstrate practical feasibility within this setting, further investigation is required to assess performance in more complex environments, such as multi-department systems, extended scheduling horizons, or larger workforce sizes.

Furthermore, the observed computational time reflects the implementation of the DDPFA within a CP-SAT-based optimization framework. Therefore, the reported computation time should be interpreted as implementation-specific performance within the evaluated computational setting rather than solely the intrinsic efficiency of the algorithm.

The results of this study also provide actionable insights for hospital workforce planning. Hospitals may consider evaluating controlled workforce reduction strategies combined with limited overtime allocation as a potential approach to improving cost efficiency while maintaining scheduling feasibility under operational conditions similar to those evaluated in this study. In addition, the model can support the design of shift allocation policies that maintain balanced workload distribution, reduce staff fatigue, and improve job satisfaction. The approach also supports evaluation of alternative staffing strategies, including overtime-limit adjustments and contract-based working-hour policies, to achieve balanced trade-offs between workload distribution and cost efficiency. However, these insights are derived from specific hospital units and scenarios, and their applicability to other healthcare settings depends on institutional policies, staffing structures, and operational complexity. The proposed approach is more applicable to hospitals with similar workforce regulations, contract structures, and shift systems, and should not be interpreted as universally generalizable. Further validation across diverse hospital environments is recommended.

4. CONCLUSION

This study developed and evaluated a DDPFA-based nurse scheduling framework that integrates nurse qualification and employment-contract constraints within a hospital operational setting. The framework generates feasible schedules while maintaining balanced workload distribution across shifts and nurses.

The performance evaluation considered four indicators: inter-shift fairness, inter-nurse fairness, soft-constraint compliance, and computation time. The results indicate that the DDPFA-based scheduling framework achieved balanced workload distribution, satisfied soft constraints, and generated feasible schedules with relatively low computation time compared with the evaluated manual scheduling and goal-programming approaches. In addition, the framework supported workforce-reduction scenarios for cost-efficiency analysis under the evaluated operational conditions.

The primary contribution of this study lies in extending the applicability of DDPFA to a nurse scheduling environment that simultaneously considers qualification requirements, employment-contract constraints, fairness objectives, and workforce-planning considerations. The findings demonstrate the practical applicability of integrating fairness-driven allocation with constraint-based scheduling to support operational decision-making in hospital workforce planning. These findings indicate that the proposed framework can support practical workforce planning by integrating fairness-driven allocation with constraint-based scheduling while maintaining operational feasibility and computational tractability under realistic hospital scheduling conditions.

This study has several limitations. First, this study was conducted using data from a single hospital under deterministic operational conditions and does not explicitly incorporate individual nurse preferences or uncertainty in workforce availability and service demand. Second, the weighting scheme for soft constraints was determined based on operational priorities and expert judgment and was not subjected to formal sensitivity analysis. Third, the cost-efficiency analysis employed a simplified direct labor cost model based on a uniform monthly salary and standard overtime compensation and did not consider additional payroll components such as night-shift allowances, weekend or holiday premiums, or institution-specific compensation policies.

Future research may extend this work through preference-based scheduling, stochastic or robust optimization models, multi-institution validation, sensitivity or ablation analysis, benchmarking against advanced metaheuristic approaches such as VNS, GA, SA, and ALNS, and more comprehensive payroll modeling. These extensions would provide a broader assessment of the framework's applicability across diverse healthcare environments.

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