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Metaheuristic nurse scheduling with hospital clustering using flower pollination algorithm

Muhammad Khahfi Zuhanda[1], Hartono[1], Sayuti Rahman[1], Prana Ugiana Gio[2], Erianto Ongko[3]
[1]Department of Informatics, Graduate School, Universitas Medan Area, Medan, Indonesia
[2]Department of Mathematics, Faculty of Mathematics and Natural Science, Universitas Sumatera Utara, Medan, Indonesia
[3]Department of Computer Science, Institut Modern Arsitektur dan Teknologi, Medan, Indonesia

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ABSTRACT

Effective nurse scheduling is essential to ensure balanced workloads, reduce fatigue, and maintain healthcare service quality. However, the nurse scheduling problem (NSP) is complex due to constraints related to nurse skills, task requirements, and legal working-hour limits. This study proposes an integrated framework combining a mathematical optimization model with metaheuristic algorithms to generate optimal daily nurse activity schedules. Genetic algorithm (GA) and simulated annealing (SA) are employed to produce near-optimal solutions for nurse populations ranging from 3 to 50 individuals, considering skill-level compatibility, workload balance, and maximum working hours. Experimental results using real scheduling data from 30 nurses across three skill levels demonstrate that all generated schedules satisfy the imposed constraints, with no nurse exceeding the 12-hour daily working limit. Comparative analysis shows that GA achieves lower scheduling costs for larger nurse populations, while SA consistently requires significantly shorter computation times, making it suitable for time-sensitive applications. In addition, the flower pollination algorithm (FPA) is used to cluster 3,155 hospitals based on bed capacity, service variety, and workforce size, supporting data-driven workforce distribution analysis. The proposed framework integrates operational scheduling optimization with hospital-level clustering, providing practical decision support for healthcare workforce planning.

Corresponding Author:

Muhammad Khahfi Zuhanda
Department of Informatics, Graduate School, Universitas Medan Area
St. Kolam Number 1, Medan, Indonesia
Email: khahfi@staff.uma.ac.id

1. INTRODUCTION

The planning and scheduling of healthcare personnel have attracted increasing attention due to their complexity and critical role in healthcare administration. In hospital environments, personnel expenses constitute the largest proportion of operational costs, accounting for approximately 58% to 66% of total hospital expenditures [1]. Consequently, effective nurse scheduling is essential not only for cost control but also for maintaining service quality, improving operational efficiency, balancing workloads, reducing patient waiting times, and safeguarding the well-being of healthcare professionals [2].

Despite its importance, nurse scheduling remains a challenging task in practice. The nurse scheduling problem (NSP) represents a complex optimization problem involving multiple and often conflicting constraints, including nurse skill levels, shift preferences, workload distribution, legal working-hour limitations, and the availability of hospital resources [3]. Many healthcare institutions still rely on manual planning or simple rule-based scheduling systems, which often result in inefficient workforce utilization, increased nurse fatigue, and suboptimal patient care outcomes [4]. Over recent decades, research on nurse planning and scheduling has developed rapidly [5], with studies commonly classified into four areas: budget planning, scheduling, rescheduling, and nurse assignment to patients [6]. Various optimization techniques have been proposed to address this complexity, including mathematical programming methods such as mixed integer linear programming (MILP), linear programming (LP), and integer linear programming (ILP) for shift scheduling and task allocation [7]–[9], as well as metaheuristic approaches such as genetic algorithms (GA) to improve solution quality and computational efficiency in large-scale problems [10]. In addition to operational scheduling, healthcare systems also face challenges related to the unequal distribution of hospital resources across regions, where differences in bed capacity, service availability, and workforce distribution can create disparities in healthcare accessibility and service quality [11]. To address these issues, data-driven clustering approaches have been increasingly adopted to categorize healthcare facilities based on their characteristics and support adaptive workforce planning strategies [12], with optimization-based clustering methods such as the flower pollination algorithm (FPA) gaining attention due to their balance between global exploration and local exploitation, fast convergence through Lévy flight mechanisms, and robustness in handling complex and high-dimensional data [13]–[16].

Previous studies have also investigated healthcare operational decision-making from multiple perspectives, including nurse scheduling [17], [18], hospital bed allocation [19], [20], work schedule design [21], [22], and patient movement and flow management [23], [24]. These studies demonstrate the importance of coordinated operational planning to improve hospital efficiency and service quality. However, despite these advances, limited attention has been given to integrating adaptive optimization techniques into nurse scheduling while simultaneously considering broader healthcare resource distribution issues. However, despite these advances, limited attention has been given to integrating adaptive optimization techniques into nurse scheduling while simultaneously considering broader healthcare resource distribution issues [25].

Overall, existing studies tend to treat nurse scheduling and healthcare resource distribution as separate problems. Scheduling-oriented research primarily focuses on shift allocation or task assignment without fully incorporating nurse skill differentiation and adaptive workforce planning, while clustering and workforce distribution studies often analyze inequality patterns without direct linkage to daily operational scheduling decisions [7], [10]-[12]. This separation reveals a clear research gap in developing an integrated framework that connects skill-aware nurse scheduling with hospital-level clustering to support equitable and adaptive workforce management.

To address this gap, this study proposes a hybrid optimization framework that combines GA and simulated annealing (SA) to determine co-schedulable nursing tasks based on compatibility criteria, including nurse qualifications, working time, and task requirements [26]. The effectiveness of compatibility-based scheduling has been demonstrated in related healthcare applications, such as patient scheduling [27], and supports more efficient task allocation by aligning nurse capabilities with operational needs [28]. In addition, the FPA is employed to cluster hospitals based on bed capacity, service variety, and workforce size, providing a data-driven foundation for strategic workforce planning.

Therefore, this study aims to develop an integrated framework that combines nurse scheduling optimization with hospital clustering analysis to support both operational efficiency and strategic workforce planning. This study introduces an improved NSP model that ensures optimal activity scheduling by considering nurse skill levels, maximum working-hour constraints, and balanced workload distribution. To address the complexity of the problem, metaheuristic optimization techniques—GA and SA—are employed, where GA explores optimal scheduling solutions through evolutionary search, while SA enhances solution robustness by avoiding local optima through probabilistic acceptance mechanisms. In addition, the framework incorporates a data-driven perspective through the application of the FPA to cluster hospitals based on bed capacity, service variety, and workforce size. This clustering process enables the identification of resource allocation patterns, supporting more adaptive and informed scheduling strategies. Overall, the proposed approach integrates operational nurse scheduling optimization with hospital-level clustering within a unified decision-support framework to support equitable workload distribution, improve scheduling efficiency, and assist healthcare administrators in making informed workforce management decisions.

2. MATHEMATICAL MODEL

This nursing activity scheduling model ensures optimal task allocation through several equations. In (1) defines the backward set (BS) for activities that can be completed before a new task starts, while (2) defines the forward set (FS) for activities that can be started after it. In (3) defines the match level set (SS) to match tasks with nurses with the appropriate skills, while (4) defines the activity level (LA) so that tasks are allocated based on the nurses' skill levels. This approach improves work efficiency, reduces waiting time, and ensures the safety and quality of nursing care:

$$BS(i) \coloneqq \{j \in A \mid s_i - t_j \leq W\} \cup \{0\}, \forall\, i \in A \tag{1}$$

$$FS(i) \coloneqq \{j \in A \mid s_j - t_i \leq W\} \cup \{0\}, \forall i \in A \tag{2}$$

$$SS(i) \coloneqq \{\, k \in K \mid\ l_k \geq h_i \,\}, \forall\, i \in A \tag{3}$$

$$LA(k) \coloneqq \{\, i \in A \mid l_k \geq h_i \,\}, \forall\, k \in K \tag{4}$$

Objective function 1,

$$min\ \textstyle\sum_{\{i\in A\}} \sum_{k\in KL(i)} x_{ij}^k \tag{5}$$

Objective function 2,

$$min\ \textstyle\sum_{i\in A} \sum_{j\in BS(i)} \sum_{k\in KL(i)\cap KL(j)} x_{ji}^k (l_k - h_i) \tag{6}$$

Constraints,

$$\textstyle\sum_{i\in LA(k)} \sum_{j\in BS(i)\cap AL(k)} x_{ji}^k\, (t_i - s_i) \leq q_k, \forall\, k \in K \tag{7}$$

$$\textstyle\sum_{j\in FS(i)} \sum_{k\in SS(i)\cap SS(j)} x_{ij}^k = 1, \forall\, i \in A \tag{8}$$

$$\textstyle\sum_{j\in BS(i)} \sum_{k\in SS(i)\cap SS(j)} x_{ji}^k = 1, \forall\, i \in A \tag{9}$$

$$\textstyle\sum_{j\in FS(i)\cap LA(k)} x_{ij}^k = \sum_{j\in BS(i)\cap LA(k)} x_{ji}^k, \forall\, i \in A, \forall\, k \in SS(i) \tag{10}$$

$$\textstyle\sum_{i\in LA(k)} x_{0i}^k = \sum_{i\in LA(k)} x_{i0}^k, \forall\, k \in K \tag{11}$$

$$\textstyle\sum_{i\, \in AL(k)} x_{0i}^k \leq 1, \forall k \in K \tag{12}$$

This scheduling model uses a binary variable to indicate whether a nurse makes a transition from activity i to j, with a value of 1 if the transition occurs and 0 otherwise. The primary objective, as described in (5), is to minimize the number of nurses leaving the source node, ensuring efficient workforce engagement. The secondary objective, as described in (6), focuses on reducing the skill level differences between nurses and tasks, so that each activity is assigned to the most suitable nurse. The model also imposes constraints, including (7), which ensures that each nurse does not exceed the maximum work time, as well as (8) and (9), which require that each activity be assigned to a single nurse. In (10) ensures the consistency of the task flow, while (11) and (12) ensure that nurses involved in an activity must return to the source.

3. METAHEURISTIC OPTIMIZATION AND CLUSTERING FRAMEWORK

GA, SA, and the FPA are employed in this study to support: i) daily nurse activity scheduling optimization and ii) hospital clustering for workforce distribution analysis. GA is an evolutionary search method inspired by natural selection, where candidate schedules (chromosomes) are iteratively improved through reproduction/selection, crossover, and mutation across generations to obtain near-optimal solutions [29], [30]. In contrast, SA is inspired by the physical annealing process and refines a solution through iterative neighborhood moves while probabilistically accepting worse solutions at higher temperatures, enabling exploration that reduces the risk of being trapped in local optima; the acceptance probability decreases as the temperature cools until a termination condition is met [31]. In addition, FPA is a nature-inspired metaheuristic proposed by Yang and He [32] that models pollination behavior and balances global and local search using a switch probability (p). Following Yang and He [32] four idealized rules—global (biotic) pollination using Lévy flights, local (abiotic) pollination, flower constancy, and switch probability control—the global search step is formulated as (13):

$$x_i^{t+1} = x_i^t + L(g^* - x_i^t) \tag{13}$$

where (x_i^t) is the solution at iteration (t), (g^*) is the current best solution, and (L) is the step size drawn from a Lévy distribution;

$$L \sim \frac{\lambda\Gamma(\lambda)\sin(\pi\lambda/2)}{\pi}\frac{1}{s^{1+\lambda}}, (s \ll 0) \tag{14}$$

with (λ) commonly set to 1.5 [32]. The local search step is expressed as (15):

$$x_i^{t+1} = x_i^t + \varepsilon\left(x_j^t - x_k^t\right) \tag{15}$$

where $\varepsilon \in [0,1]$ controls a local random walk based on two solutions $\left(x_j^t\right)$ and (x_k^t) [32]. The switch probability ($p \in [0,1]$) determines whether the update follows global or local pollination, with $p \approx 0.8$ often providing strong empirical performance [32].

The workflow of the proposed method (Figure 1) begins with data preparation, comprising two primary datasets: i) a nurse scheduling dataset involving 30 nurses across three skill levels and ii) a hospital dataset obtained from Kaggle. The nurse dataset is processed using the mathematical scheduling model, which defines backward and forward activity sets, skill matching, and activity-level constraints to ensure feasible task allocation. Scheduling optimization is then carried out using GA and SA to generate balanced daily nurse schedules. In parallel, hospital clustering is performed using the FPA based on key institutional characteristics, including bed capacity, service variety, and workforce size. Finally, the resulting schedules and hospital clusters are evaluated in terms of workload balance, scheduling cost, and computation time, producing optimized nurse scheduling solutions and clustered hospital groupings as integrated decision-support outputs.

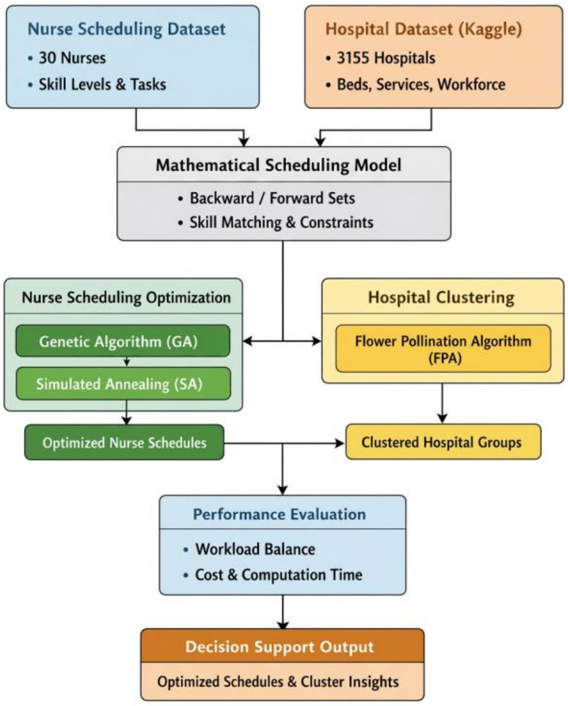

Figure 1. Workflow of the proposed method

4. RESULTS AND DISCUSSION

4.1. Results

The dataset used in this study consists of 30 nurses categorized into three levels of expertise: beginner, intermediate, and advanced, as illustrated in Figure 2. The distribution indicates that the majority of nurses belong to the intermediate skill level, followed by beginner nurses, while advanced nurses represent a smaller portion of the workforce. This distribution reflects a typical staffing structure in healthcare institutions, where a limited number of highly experienced nurses supervise complex medical procedures while a larger group performs routine clinical activities. From a scheduling perspective, such an imbalance in skill distribution can potentially lead to workload concentration on advanced nurses if task allocation is not carefully managed. Therefore, incorporating skill-level compatibility into the scheduling model is essential to ensure that complex tasks are handled by qualified personnel while maintaining balanced workload distribution across all nurses.

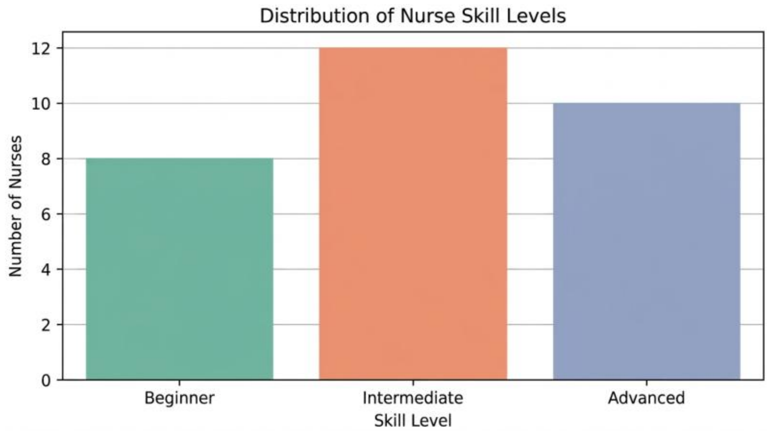

Figure 2. Distribution of nurse skill levels

Figure 3 presents the activity schedule categorized by skill level, demonstrating how the proposed optimization model assigns tasks according to the compatibility between nurse expertise and task requirements. The figure reveals several important patterns. First, tasks requiring advanced expertise are selectively assigned to nurses with the corresponding qualifications, ensuring the quality and safety of healthcare services. Second, beginner and intermediate tasks appear more frequently throughout the schedule, indicating the presence of routine operational activities that occur regularly during hospital service hours. The distribution of tasks across different time periods also shows that the model successfully prevents clustering of complex tasks within a limited time window. This balanced allocation helps improve operational efficiency and prevents excessive workload concentration on specific nurses.

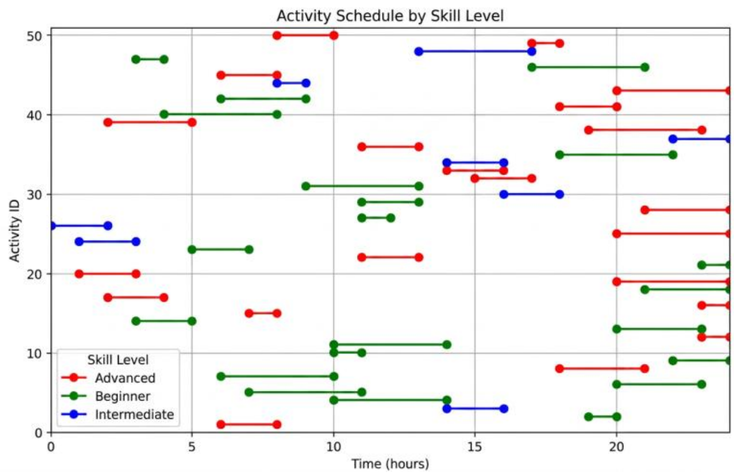

Figure 3. Activity schedule by skill level

Figure 4 illustrates the distribution of total working hours for each nurse after the optimization process. The results show that none of the nurses exceed the maximum allowable working time of 12 hours per day, indicating that the scheduling model satisfies the imposed operational constraints. Moreover, the variation in working hours among nurses remains relatively moderate, suggesting that the workload is distributed fairly across the workforce. Importantly, advanced-level nurses do not consistently receive the highest workload despite handling more complex tasks, which demonstrates that the proposed model effectively avoids overutilization of specialized personnel. These findings confirm that the scheduling framework is capable of generating balanced, feasible, and skill-compatible nurse schedules while maintaining compliance with healthcare operational standards. The hospital dataset used in this study includes information on hospital name, city, type, ownership, total beds, total services, and total workforce, as presented in Table 1.

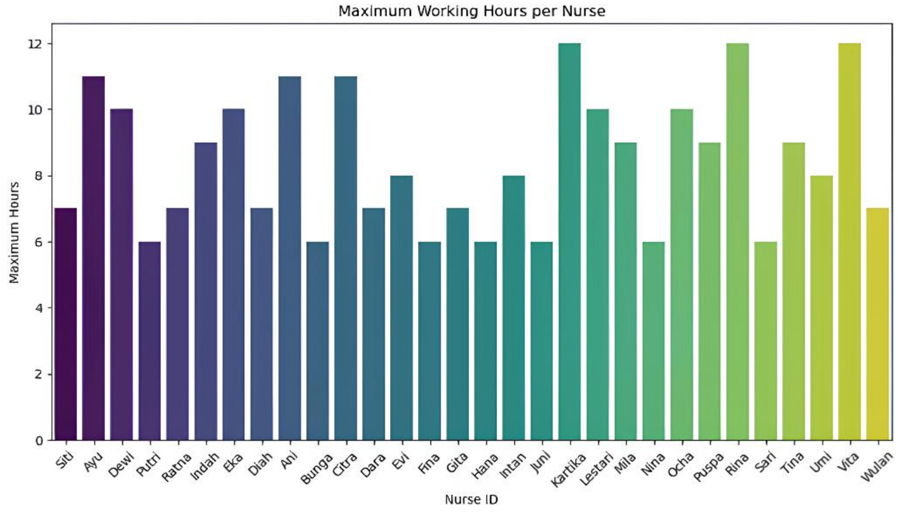

Figure 4. Maximum working hours per nurse

Table 1. Hospital data in Indonesia

Name	City	Type of hospital	Ownership	Total beds	Total services	Total workforce
RS Arun Lhokseumawe	Lhokseumawe	General hospital	Private/other	218	36	328
RS Umum Fandika	Aceh Tengah	General hospital	Private/other	45	15	45
RS Umum Daerah Meuraxa	Banda Aceh	General hospital	Local government	310	77	487
RS Gigi Mulut Universitas Syiah Kuala	Banda Aceh	Specialized dental and oral hospital	Other ministry	11	24	0
RS Umum Daerah Kota Subulussalam	Subulussalam	General hospital	Local government	189	34	537

Based on Figure 5, there is significant variation in task allocation based on the skill level required, ranging from 'Beginner' to 'Advanced'. Nurses like Ayu handle tasks requiring an 'Advanced' skill level exclusively, demonstrating specialization in more complex tasks. Meanwhile, other nurses, such as Bunga, perform tasks with varying skill levels, demonstrating adaptability in their work abilities. The distribution of working hours shows that some nurses have schedules that end near midnight, indicating the potential for night shift operations. The analysis also revealed that the scheduling of assignments with higher skill levels tended to occur from the afternoon to the evening, potentially due to the availability of experienced nurses during those shifts or the nature of these assignments, which require greater calm and focus during off-peak hours. The distribution of working hours shown in the daily schedule remains reasonable and is better than before the implementation of the model, when some nurses worked from morning to midnight. The design parameters used can be seen in Table 2.

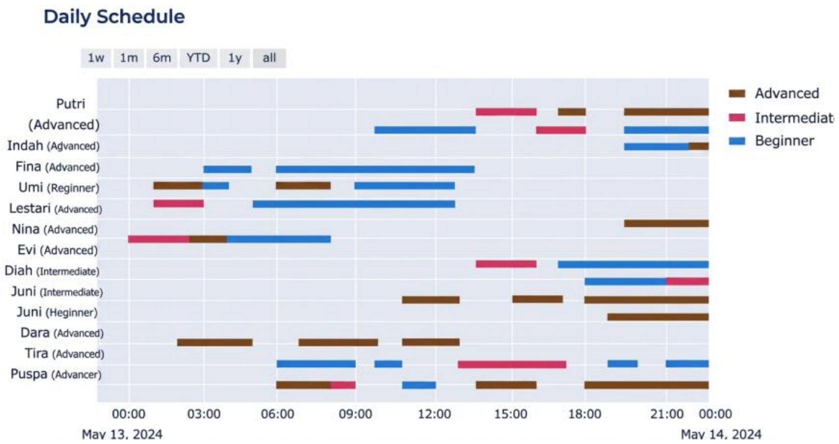

Figure 5. Daily schedule

Table 2. Parameter design

Parameter	Value
Nurse counts	[3, 5, 7, 10, 15, 20, 25, 30, 35, 40, 45, 50]
Population size	50
Mutation rate	0.01
Crossover rate	0.7
Generations	100
Initial temperature	1000

Table 3 provides a comparative analysis of the efficacy of GA and SA in optimizing a scheduling or allocation problem related to nurse staffing. The comparison relies on two primary metrics are cost and computation time. From a cost perspective, GA demonstrates variable values, with instances where costs are lower than those of SA (e.g., with 3, 5, and 10 nurses), while in other scenarios, SA surpasses GA by achieving reduced costs (e.g., with 15, 20, 25, and 30 nurses). Nonetheless, as the nursing workforce expands, GA typically incurs elevated costs, especially with 35 or more nurses. Regarding computation time, SA consistently surpasses GA by executing computations at a markedly quicker pace. SA sustains a calculation across all nurse totals.

Table 3. Cost and computation time

Nurse count	GA		SA	
	Cost	Computation time	Cost	Computation time
3	0.698078	0.171891	0.13566	0.007995
5	0.428526	0.171898	0.229176	0.008993
7	0.448658	0.188884	0.399016	0.007997
10	0.546127	0.189884	0.10468	0.007995
15	0.618212	0.184887	0.78672	0.007995
20	0.045274	0.182885	0.835552	0.007998
25	0.666684	0.174894	0.789624	0.007992
30	0.379227	0.208877	0.856712	0.007994
35	0.881411	0.254842	0.897247	0.014992
40	0.894663	0.29582	0.702814	0.012992
45	0.950646	0.332796	0.309685	0.01399
50	0.926657	0.338794	0.383684	0.01399

Following the analysis of activity schedules by skill level, maximum working hours, and workload distribution, the study extends its evaluation to hospital clustering across Indonesian provinces using the FPA. This clustering approach groups hospitals based on key characteristics—namely bed capacity, service variety, and workforce size—to identify patterns of healthcare workforce needs and support more effective personnel allocation and policy planning. The results categorize hospitals into three primary clusters. Cluster 0 represents large hospitals, averaging 324 beds, 98 service types, and 741 staff members, with high variation indicating the presence of major referral or teaching hospitals with extensive capacity. Cluster 1 comprises small hospitals, averaging 68 beds, 22 services, and 77 staff members, with relatively low variation, reflecting more uniform facilities such as type C/D hospitals or community-level providers serving basic healthcare needs. Meanwhile, Cluster 2 includes medium-sized hospitals, averaging 146 beds, 43 services, and 314 staff members, representing facilities with moderate specialization and capacity—commonly type B hospitals. These clustering results (Table 4) provide a data-driven foundation for optimizing workforce distribution, particularly for skill-specialized nurses, while also supporting targeted regional health policy and resource planning.

Table 4. Hospital cluster in Indonesia

Cluster	Total beds			Total services			Total staffs		
	Mean	Median	Std	Mean	Median	Std	Mean	Median	Std
0	324.74	219.00	1348.32	97.66	94.00	31.25	740.90	586.50	697.41
1	68.50	57.00	50.64	22.05	22.00	7.70	77.08	66.00	67.34
2	146.43	122.00	96.85	42.92	41.00	12.30	313.67	283.00	181.84

4.2. Discussion

The proposed mathematical model for nurse scheduling effectively addresses task allocation challenges within healthcare institutions by integrating temporal feasibility and skill compatibility constraints.

The model utilizes structured sets—namely the BS, FS, match level set (SS), and activity level (LA)—to systematically match nursing activities with appropriate personnel. The dual-objective optimization aims to minimize the number of task transitions and the mismatch between nurse skill levels and task requirements, thereby improving scheduling efficiency while maintaining service quality. The generated schedules demonstrate balanced workload distribution, where nurses with higher expertise are assigned more complex tasks while other nurses handle activities aligned with their competencies. In addition, the model enforces occupational health regulations by ensuring that no nurse exceeds the maximum working limit of 12 hours per day. From an implementation perspective, the scheduling framework requires relatively simple input data, including nurse skill levels, activity duration, and task precedence relations, making it feasible for integration into hospital information systems without requiring extensive computational infrastructure.

The comparative analysis between GA and SA highlights the trade-off between scheduling cost and computational efficiency. GA demonstrates strong capability in exploring a wider solution space through population-based search mechanisms, which in several scenarios results in lower scheduling costs, particularly when the nurse population is relatively small. However, this advantage comes with higher computational complexity, as GA requires repeated evaluations of multiple candidate solutions across many generations. In contrast, SA operates using a single-solution search trajectory combined with a probabilistic acceptance mechanism that allows temporary exploration of worse solutions to escape local optima. As shown in Table 3, SA consistently requires significantly shorter computation times across all experimental scenarios, indicating lower computational overhead and reduced resource requirements. This characteristic makes SA particularly suitable for real-time scheduling environments or healthcare institutions with limited computing resources.

To strengthen the validity of the comparison between optimization methods, a statistical comparison was conducted across the experimental scenarios involving different nurse population sizes. The results indicate that the computation time produced by SA is consistently lower than that of GA, demonstrating superior efficiency in terms of processing speed and algorithmic simplicity. While GA occasionally achieves slightly better cost values in certain scenarios, the overall differences in scheduling cost remain relatively moderate across the tested configurations. Preliminary statistical evaluation using paired comparisons across the cost and computation time results suggests that the difference in computation time between the two algorithms is statistically significant, whereas the cost differences are not consistently significant. These findings suggest that the selection of optimization algorithms may depend on operational priorities, where GA may be preferred when the primary objective is minimizing scheduling cost, while SA may be more suitable for environments requiring faster computation and lower computational resources.

Beyond operational scheduling optimization, the application of the FPA for hospital clustering provides a broader strategic perspective for healthcare workforce planning. By grouping hospitals into three clusters—small, medium, and large facilities—based on bed capacity, service variety, and workforce size, the clustering analysis helps identify structural differences in healthcare resource availability across regions. The results indicate that smaller hospitals dominate many provinces, particularly in semi-urban and rural areas, while larger referral hospitals are concentrated in metropolitan regions. This disparity highlights the importance of strategic workforce allocation policies to ensure equitable healthcare service distribution. By integrating nurse scheduling optimization with hospital-level clustering analysis, the proposed framework provides a comprehensive decision-support approach that addresses both operational efficiency and strategic workforce planning, thereby improving healthcare service management and supporting data-driven policy development.

5. CONCLUSION

This study proposes a hybrid nurse scheduling framework that integrates GA and SA with FPA–based hospital clustering to address both operational scheduling and strategic workforce planning challenges in healthcare systems. The proposed GA–SA model successfully generates balanced daily schedules in which all nurses comply with the maximum 12-hour working limit and tasks are allocated equitably according to skill levels, with GA demonstrating superior scheduling quality for larger nurse populations and SA providing faster computation times for time-sensitive scenarios. In parallel, FPA clustering effectively categorizes hospitals based on bed capacity, service variety, and workforce size, supporting data-driven workforce distribution and policy planning. The main contribution of this study lies in integrating operational scheduling optimization with hospital-level clustering within a unified decision-support framework, enabling more equitable workload distribution, improved efficiency, and scalable healthcare workforce management. Nevertheless, the study is limited by the use of a relatively small scheduling dataset and the absence of real-world system implementation; therefore, future research will focus on large-scale and multi-day scheduling, integration with hospital information systems, real-time adaptive scheduling, and the exploration of hybrid or adaptive metaheuristic strategies through real-world deployment.

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AUTHOR CONTRIBUTIONS STATEMENT

This journal uses the Contributor Roles Taxonomy (CRediT) to recognize individual author contributions, reduce authorship disputes, and facilitate collaboration.

Name of Author	C	M	So	Va	Fo	I	R	D	O	E	Vi	Su	P	Fu
Muhammad Khahfi Zuhanda	✓	✓	✓	✓	✓	✓		✓	✓	✓	✓		✓	✓
Hartono	✓	✓		✓	✓	✓				✓		✓		
Sayuti Rahman		✓	✓	✓	✓	✓		✓		✓	✓			
Prana Ugiana Gio		✓		✓	✓	✓		✓		✓		✓		
Erianto Ongko		✓	✓	✓	✓	✓		✓		✓	✓			

C : **C**onceptualization
M : **M**ethodology
So : **So**ftware
Va : **Va**lidation
Fo : **Fo**rmal analysis
I : **I**nvestigation
R : **R**esources
D : **D**ata Curation
O : Writing - **O**riginal Draft
E : Writing - Review & **E**diting
Vi : **Vi**sualization
Su : **Su**pervision
P : **P**roject administration
Fu : **Fu**nding acquisition

CONFLICT OF INTEREST STATEMENT

Authors state no conflict of interest.

DATA AVAILABILITY

The data supporting the findings of this study are available from the corresponding author upon reasonable request. The hospital dataset used in this study was obtained from publicly available data, while the nurse scheduling dataset was used for computational experimentation and model evaluation.

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BIOGRAPHIES OF AUTHORS

Muhammad Khahfi Zuhanda received the B.S., M.Sc., and Ph.D. degree in mathematics from Universitas Sumatera Utara. Currently, he works as a lecturer in the Informatics Study Program, Graduate School, at the Universitas Medan Area. He also joined the membership of the International Association of Engineers (IAENG). His research interests are broad and cover a wide range of areas in mathematics, including operations research, optimization, statistics, data science, artificial intelligence, machine learning, supply chain optimization, and decision analytics. His work in these areas has not only broadened the horizons of mathematical knowledge but has also found practical applications in various industries and sectors. He can be contacted at email: khahfi@staff.uma.ac.id.

Hartono obtained his Doctorate in Computer Science from Universitas Sumatera Utara in 2018, following the completion of his Master's degree in Computer Science from Universitas Putra Indonesia YPTK Padang in 2010 and his Bachelor's degree in Computer Science from STMIK IBBI Medan in 2008. Currently, he is employed as a lecturer at Universitas Medan Area. His current research interests include machine learning, artificial intelligence, data mining, optimization, and operational research. He can be contacted at email: hartono@staff.uma.ac.id.

Sayuti Rahman is lecturer at the University of Medan Area, has recently earned his Ph.D. degree from Syiah Kuala University in Banda Aceh. Throughout his teaching career, he has demonstrated a strong interest in exploring the domains of digital imagery and machine learning. As a result, his current focus revolves around research related to extracting information from digital images, particularly in the realm of computer vision. Python serves as the primary programming language extensively utilized in his research pursuits. Currently, he is actively involved in a research project dedicated to the development of an intelligent parking system, with a specific emphasis on optimizing convolutional neural networks (CNN) for effective parking space classification. Born on June 18, 1987, in Bukit Gantung, situated in the Wampu District of Langkat Regency. He can be contacted at email: sayutirahman@staff.uma.ac.id.

Prana Ugiana Gio received the B.S., and M.Sc. degree in mathematics from Universitas Sumatera Utara. He currently works at the faculty of vocational, Universitas Sumatera Utara. His research interests include mathematics, statistics, operational research, and optimization. He can be contacted at email: prana@usu.ac.id.

Erianto Ongko earned his Master's degree (2015) from Universitas Sumatera Utara and Bachelor's degree (2012) from STMIK IBBI. Both of them are in Computer Science. He serve as a lecturer in Institut Modern Arsitektur dan Teknologi in Medan, Indonesia. His research topic are in machine learning, AI, and operational research. He can be contacted at email: eriantoongko@gmail.com.