Optimizing Staff Scheduling in Blood Production: A Case Study of Hospital X in Vietnam

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Abstract: ***Blood management is a critical healthcare operation, yet its workforce planning remains challenging due to unpredictable demand and limited staffing. This case study examines Hospital X in Vietnam, where persistent overtime and uneven shift allocations affect staff wellbeing and operational sustainability. To address these challenges, the study proposes a Mixed-Integer Linear Programming model to optimize schedules and minimize overtime. Additionally, a Genetic Algorithm is employed as a heuristic to generate feasible solutions efficiently. The methodology was validated using both synthetic data and real operational data from Hospital X. Results indicate improved workload balance and reduced overtime, offering a practical framework for workforce planning in blood preparation and distribution units.***

Keywords: Workforce Scheduling, Blood Bank Operations, Healthcare Logistics, Mixed-Integer Linear Programming, Genetic Algorithm

1. Introduction

Blood is a valuable and irreplaceable resource that relies entirely on human donation. Blood and blood products play a critical role in medicine, contributing to the survival of millions of patients each year suffering from life-threatening conditions and enabling complex medical and surgical procedures. However, blood and its derivatives are also highly susceptible to spoilage, contamination, and infection [1]. Blood products refer to any therapeutic substance derived from human blood, including whole blood, blood components for transfusion, and plasma-derived medicinal products. Transfusable components obtained from donated blood include red blood cells, platelets, plasma, cryoprecipitate AHF (cryo), and granulocytes. The processes of receiving, transporting, and storing blood are essential to maintaining the quality and availability of blood for transfusion. These interconnected activities form what is known as the Transfusion Blood Supply Chain, as illustrated in Figure 1.

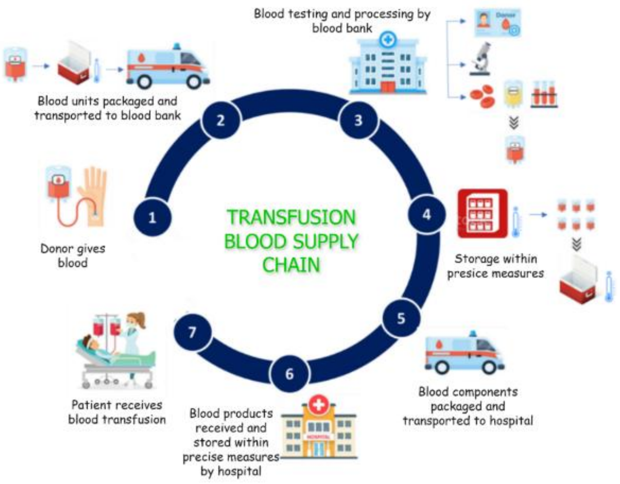

Figure 1: Transfusion blood supply chain

There is currently a lot of research and investment in the use of smart technologies, artificial intelligence, and robotics to reduce errors in the process of collecting, managing, preserving, and using blood, especially automating some steps and processes, to increase safety and efficiency for blood banks ([2] and [3]). Despite these advancements, significant challenges persist in blood bank operations. One critical issue is the frequent need for staff to work overtime. According to Vietnamese labor law, there is a legally defined annual limit on overtime hours to prevent labor exploitation. However, staff in this department often exceed this limit, resulting in many unpaid overtime hours. Furthermore, employees have expressed concerns about substantial disparities in their weekly and monthly working hours, largely due to inefficient scheduling.

This study addresses three key challenges in operational planning and human resource allocation in blood banks: (1) developing a model to determine the required workforce to meet blood production demands; (2) optimizing staff schedules for accurate and efficient allocation; and (3) assigning tasks effectively to align with available resources and minimizing overtime and scheduling imbalances. The significance of this study lies in its potential to enhance workforce sustainability and operational efficiency in healthcare services, particularly in critical blood production units facing staffing constraints.

The remainder of the paper is organized as follows: Section 2 reviews relevant literature; Section 3 presents a detailed problem description and mathematical model; Section 4 introduces the experimental design and case study at Hospital X; and Section 5 concludes with key findings, implications, and recommendations.

2. Related literature

Scheduling and rostering involve allocating human, material, financial, and temporal resources to effectively achieve organizational objectives. In the healthcare sector – particularly hospitals – this has long been a key research area, with major benchmarks such as the International Nurse Rostering Competitions (INRC-I in 2010 and INRC-II in 2014).

Many studies focus on single-objective models due to the complexity of the constraints. A common objective is minimizing penalty costs for soft constraint violations, as seen in works such as [4]–[11]. Others, like [12], aim to reduce labor costs (e.g., base wages, overtime), while [13] target minimizing unmet staff change requests.

In contrast, some researchers have pursued integrated objective functions, simultaneously addressing staff assignment and task allocation ([14]–[16]). Although more complex, this approach is gaining popularity thanks to advances in solving simpler and sequential formulations.

Given the NP-hard nature of rostering problems [17], exact methods such as MILP are practical only for small to medium instances ([12], [18]). For larger datasets, researchers rely on metaheuristics, rule-based heuristics, and AI methods. Notable examples include the rolling horizon algorithm and iterative shift selection algorithm [14], and a column generation approach [13], which offer efficient and scalable performance. Hybrid algorithms have shown great potential by combining exact and heuristic techniques. For example, [8] and [19] integrated MILP, constraint programming, and variable neighborhood search for greater accuracy. Similarly, [7] introduced a multi-phase method combining Fix-and-Relax, Simulated Annealing, and Fix-and-Optimize, yielding several best-known solutions.

Other innovative hybrid approaches include the Artificial Bee Colony with Hill Climbing [9], and Sequence-based Selection Hyper-Heuristics [20]. Recently, machine learning and artificial intelligence have emerged as powerful tools. For instance, [6] developed a neural network–based method to automate heuristic design, combining deep neural networks (DNNs) and recurrent neural networks (RNNs) to guide reconstruction and escape local optima – outperforming several deep reinforcement learning baselines.

Recent studies show a shift in human resource planning from single- to multi-objective problem solving. While multi-objective models are more complex, metaheuristics, rule-based heuristics, and AI methods offer practical solutions, especially for large or uncertain datasets. Hybrid approaches combining these techniques improve both flexibility and accuracy. However, many existing methods are still complex and not easily adaptable for planners. Integrating AI with heuristics offers a promising, flexible, and stable approach – capable of adjusting to changing objectives and delivering high quality solutions efficiently.

Consequently, this research including the MILP and metaheuristics (GA) to address the problem of the case study at Hospital X.

3. Problem Description

3.1 Mathematical model

To address the challenges of workforce scheduling and task allocation in blood banks, we define the following sets and constraints to represent the problem mathematically and guide model formulation.

Let E= {1, …, e} be the set of employees, J = {1, …, j} be the set of tasks to be accomplished, D = {1, …, d} be the set of days that constitutes the time horizon, S = {1, …, s} be the set of shifts and W = {1, …, w} be the set of week in month. Each employee is assigned exactly one role, but a role can encompass multiple tasks. For instance, a regular staff member may be responsible for receiving, preparation, labeling, or evaluation. However, to simplify the problem, staff roles will be assigned manually, as there are only two types of staff. Each employee is assigned to only one shift per day. Therefore, the parameter ES_{es} will define if staff can work in shift or not. Additionally, some tasks are restricted to specific days of the week. For example, transporting blood to external locations may only be possible on Monday, Wednesday, or Friday afternoons, or on Tuesday, Thursday, or Saturday mornings. Such shipments occur only when requested. The shifts in the problem may overlap with each other. For example, regular staff shifts are divided into two shifts. The first shift runs from 7:30 a.m. to 4:30 p.m., while the second shift begins at 10:00 a.m. and ends at 7:00 p.m. Each task, represented by j in J, each shift, represented by s in S, each day, represented by d in D, and each week, represented by w in W requires a specific number, denoted as $Requirement_{jsdw}$. These requirements form the task execution constraints.

An employee must have a full day off after working an on-duty shift. For example, if a regular staff member works a 24-hour shift on Monday, they must rest on Tuesday. These restrictions are collectively referred to as rest constraints.

The work schedule for each employee follows shift-based assignments; however, not all shifts have fixed start and end times. Instead, shifts are defined by constraints on the number of hours an employee can work per day or week, rather than the total number of shifts assigned per week. F^{max} represents the maximum number of times slots an employee e can work in a week. These weekly working hour constraints ensure a balanced workload among employees and are referred to as workload constraints.

Assumptions:

a) The number of weeks is concerned in the problem is 4 weeks.
b) Because the working shift between regular staff and radiation staff are different, also there are four different shifts: on duty (24 hours continuous working), administrative shift, blood transporting, and preparation shift, there will be a total of 8 shifts, set of Shifts = {1, 2, 3, 4, 5, 6, 7, 8}. In detail:
   - S1: Shift 1 of regular staff, starts from 7:30 to 16:30.
   - S2: Shift 2 of regular staff, starts from 10:00 to 19:00.
   - S3: Shift 1 of radiation staff, starts from 8:00 to 16:30.
   - S4: Shift 2 of radiation staff, starts from 11:00 to 19:00.
   - S5: blood transportation shift, morning from 7:30 to 11:30, afternoon from 13:00 to 17:00.
   - S6: preparation shift from 18:00 to 19:00.
   - S7: administrative shift
   - S8: on duty shift – 24 hours continuous working.
c) The working time for each shift will be 18, 18, 17, 16, 8, 2, 16, 48 for shift 1 to 8, respectively. However, the time for shift 7 is not considered as we will not compare the working time of staff and management.
d) Weekends and holidays are not considered in this case.
e) The required employees for job each day on the schedule is based on the description when interviewing the scheduler.

However, this value is based on blood demand. For example, if the need for blood is higher, then the requirement of employees is higher. In this case, the requirement is set at the average number as the scheduler gives.

Table 1: Notation

Sets	
E	Set of employees
J	Set of tasks
D	Set of days
S	Set of shifts
W	Set of weeks in month
$E_{Regular}$	Subset of regular staff
$E_{Radiation}$	Subset of radiation staff
E_{Admin}	Subset of admin
Parameters	
R_{jsdw}	Number of employee requirement for job j in shift s on day d in week w
ES_{es}	Suitability of employee e for shift s; $e \in E$, $s \in S$
$time_s$	The time slots of each shift (1 unit = 30 minutes)
F^{max}	The maximum number of time slots employees can work in a week (1 unit = 30 minutes)
BigM	A very large number
Decision variables	
x_{ejsdw}	1 if employee e performs task j in shift s on day d in week w; $e \in E$, $j \in J$, $s \in S$, $d \in D$, $w \in W$; 0 otherwise
u	Auxiliary variable, used for linearization constraint, $u \in \{0,1\}$
wt_{ew}	The total working time of employee e in week w; $e \in E$, $w \in W$
$z_{(e1)(e2)w}$	Auxiliary variable, define the difference time between the employees in week; $e1 \in E$, $e2 \in E$, $w \in W$, $e1 \neq e2$
y_{edw}	1 if employee e work on day d in week w; $e \in E$, $d \in D$, $w \in W$; 0 otherwise
T1	Integer variable, the value presented for the total differences in total time of regular staff in absolute value
T2	Integer variable, the value presented for the total differences in total time of radiation staff in absolute value
k_e	1 if employee e is used; $e \in E$; 0 otherwise.

A mathematical model has been developed based on the constraints referenced from the study by [21]. However, this study adopts a different objective function from that of Masini et al., as the research objectives of the two studies differ. The mathematical model is presented as follows:

$$\min Workload\ balance = T1 + T2 \quad (1)$$

subject to

$$T1 = \sum_{e1 \in E_{Regular}} \sum_{e2 \in E_{Regular}} \sum_{w \in W} z_{(e1)(e2)w} \ \ \forall e1 > e2 \quad (2)$$

$$T2 = \sum_{e1 \in E_{Radiation}} \sum_{e2 \in E_{Radiation}} \sum_{w \in W} z_{(e1)(e2)w} \ \ \forall e1 > e2 \quad (3)$$

$$z_{(e1)(e2)w} \geq wt_{(e1)w} - wt_{(e2)w} \ \forall e1, e2 \in E_{Regular}, w \in W, e1 > e2 \quad (4)$$

$$z_{(e1)(e2)w} \geq wt_{(e2)w} - wt_{(e1)w} \forall e1, e2 \in E_{Regular}, w \in W, e1 > e2 \quad (5)$$

$$z_{(e1)(e2)w} \geq wt_{(e1)w} - wt_{(e2)w} \ \forall e1, e2 \in E_{Radiation}, w \in W, e1 > e2 \quad (6)$$

$$z_{(e1)(e2)w} \geq wt_{(e2)w} - wt_{(e1)w} \forall e1, e2 \in E_{Radiation}, w \in W, e1 > e2 \quad (7)$$

$$wt_{ew} = \sum_{j \in J} \sum_{s \in S} \sum_{d \in D} x_{ejsdw} \times time_s \ \forall e \in E, w \in W \quad (8)$$

$$\sum_{e \in E} x_{ejsdw} \times ES_{es} = R_{jsdw} \quad \forall j \in J, s \in S, d \in D, w \in W \quad (9)$$

$$\sum_{e \in E} \sum_{j \in J} \sum_{s \in S} x_{ejsdw} = \sum_{j \in J} \sum_{s \in S} R_{jsdw} \quad \forall d \in D, w \in W \quad (10)$$

$$\sum_{j \in J} \sum_{s \in S} x_{ejsdw} \leq 1 \quad \forall e \in E, d \in D, w \in W \quad (11)$$

$$\sum_{e \in E_{Regular}} x_{e18dw} \times ES_{e8} = \sum_{e \in E_{Radiation}} x_{e18dw} \times ES_{e8} \ \forall d \in D, w \in W \quad (12)$$

$$\sum_{e \in E_{Regular}} x_{e18dw} \times ES_{e8} + \sum_{e \in E_{Radiation}} x_{e18dw} \times ES_{e8} = R_{18dw} \ \forall d \in D, w \in W \quad (13)$$

$$x_{ej8dw} \times ES_{e8} = 1 + BigM(1 - u1) \ \forall e \in E, d \in \{1, \dots, D-1\}, w \in W \quad (14)$$

$$\sum_{j \in J} \sum_{s \in S} x_{ejs(d+1)w} \leq BigM(1 - u2) \forall e \in E, d \in \{1, \dots, D-1\}, w \in W \quad (15)$$

$$u2 \geq u1 \quad (16)$$

$$x_{ej87w} \times ES_{e8} = 1 + BigM(1 - u3) \ \forall e \in E, w \in \{1, \dots W-1\} \quad (17)$$

$$\sum_{j \in J} \sum_{s \in S} x_{ejs1(w+1)} \leq BigM(1 - u4) \ \forall e \in E, w \in \{1, \dots W-1\} \quad (18)$$

$$u4 \geq u3 \quad (19)$$

$$\sum_{j \in J} \sum_{s \in S} x_{ejsdw} = 1 + BigM(1 - u5) \ \forall e \in E, d \in D, w \in W \quad (20)$$

$$y_{edw} = 1 + BigM(1 - u6) \ \forall e \in E, d \in D, w \in W \quad (21)$$

$$u6 \geq u5 \quad (22)$$

$$x_{ej4dw} = 1 + BigM(1 - u7) \ \forall e \in E_{Radiation}, j \in J, s \in S, d \in D, w \in W \quad (23)$$

$$\sum_{j \in J} \sum_{t1=1}^{7-d} x_{ej4(d+t1)w} \leq BigM(1 - u8) \ \forall e \in E_{Radiation}, s \in S, d \in D, w \in W \quad (24)$$

$$u8 \geq u7 \quad (25)$$

$$x_{e75dw} = 1 + BigM(1 - u9) \ \forall e \in E, j \in J, s \in S, d \in D \backslash \{7\}, w \in \{1, \dots W-2\} \quad (26)$$

$\sum_{t1=1}^{7-d} x_{e75(d+t1)w} + \sum_{t2=1}^{7} x_{e75(t2)(w+1)} + \sum_{t3=1}^{d} x_{e75(t3)(w+2)} \leq BigM(1-u10)\ \forall e \in E, j \in J, s \in S, d \in D\backslash\{7\}, w \in \{1, \dots W-2\}$ (27)

$u10 \geq u9$ (28)

$x_{e226w} = 1 + BigM(1-u11)\ \forall e \in E_{Regular} \cup E_{Admin}, w \in \{1, \dots W\}$ (29)

$x_{e227w} \leq BigM(1-u12)\ \forall e \in E_{Regular} \cup E_{Admin}, w \in \{1, \dots W\}$ (30)

$u12 \geq u11$ (31)

$x_{e227w} = 1 + BigM(1-u13)\ \forall e \in E_{Regular} \cup E_{Admin}, w \in \{1, \dots W-1\}$ (32)

$x_{e226(w+1)} \leq BigM(1-u14)\ \forall e \in E_{Regular} \cup E_{Admin}, w \in \{1, \dots W-1\}$ (33)

$u14 \geq u13$ (34)

$wt_{ew} \leq F^{max}\ \forall e \in E, w \in W$ (35)

$x_{ejsdw} \in \{0,1\}\quad \forall\ e \in E, j \in J, s \in S, d \in D_j, w \in \mathrm{W}$ (36)

$\mathrm{y_{edw}} \in \{0,1\}\ \ \forall\ e \in E, d \in D_j, w \in \mathrm{W}$ (37)

$wt_{ew} \geq 0, integer\ \ \forall\ e \in E, w \in \mathrm{W}$ (38)

$\mathrm{z_{(e1)(e2)w}} \geq 0, integer\ \ \forall\ e1, e2 \in E, w \in \mathrm{W}$ (39)

$T1, T2 \geq 0, integer$ (40)

$u1, u2, u3, u4, u5, u6, u7, u8, u9, u10, u11, u12, u13, u14 \in \{0,1\}$ (41)

The objective function of this problem is to minimize the total difference in working hours among regular staff (T1) and radiation staff (T2). Constraints (2) – (8) handle the computation of T1 and T2. Constraints (9) – (34) ensure that all scheduling requirements are met. Constraints (9) and (10) are to ensure that the number of assigned employees matches the required workforce. This is achieved by multiplying x with ES to guarantee that employee e is assigned only to shifts they are eligible to work. Constraint (11) ensures that each employee is assigned to exactly one shift for one job per day. Constraints (12) and (13) enforce the on-duty shift will have one regular staff and one radiation staff. Constraints (14) – (19) ensure that if an employee is assigned to an on-duty shift on day d, they must have the following day off. Specifically, constraint (14) – (16) applies this rule to weekdays, while constraint (17) – (19) extends it to the end of the week. Constraint (20) – (22) introduced to count the number of employees scheduled for workforce planning. Constraint (23) – (25) help rotationally assign radiation staff to their shift 2. Constraint (26) – (28) is for delivery tasks, which all employees rotate this job. Constraints (29) – (34) are the same as constraint (23) – (25), but for the regular staff and admin on the weekend. Constraint (35) restricts weekly working hours for each employee. Finally, constraints (20) – (44) facilitate the transformation of the problem from a MINLP model to a MILP model through linearization of nonlinear constraints. Finally, Constraints (36) – (41) define the ranges of the variables of the problem.

To address overtime concerns, a new objective function estimates the minimum staffing required to meet operational needs without excessive workloads. This helps determine the minimum workforce needed to meet operational demands and ensures the main scheduling model receives adequate human resource input. A supporting mathematical sub-model is thus developed to estimate staffing needs and enable feasible, effective scheduling.

$$\min Total\ employees = \sum_{e \in E} k_e \quad (42)$$

subject to

(9) – (41)

$$\sum_{j \in J} \sum_{s \in S} \sum_{d \in D} \sum_{w \in W} x_{ejsdw} = 1 + BigM(1-u15)\ \forall e \in E \quad (43)$$

$$k_e = 1 + BigM(1-u16) \forall e \in E \quad (44)$$

$$u16 \geq u15 \quad (45)$$

$$k_e \in \{0,1\}\quad \forall\ e \in E \quad (46)$$

$$u15, u16 \in \{0,1\} \quad (47)$$

3.2 Genetic Algorithm

As genetic algorithms are considered, which can be used for applications of sample data and large real-case data. Although the genetic algorithm is widely used, there are some essential modifications that need to be made to be suitable for the case concerned. The flow chart below shows the step for solving the problem by GA.

The GA illustrated in Figure 2 follows a standard evolutionary process – starting with a generated initial population, evaluating fitness, applying selection, crossover, and mutation operations, and iteratively updating the population until a termination condition is met. At each stage, a feasibility check is performed to ensure that the final solution remains valid upon termination. The first stage, Initial Population, creates a population of feasible solutions rather than purely random ones. In the selection stage, tournament selection is applied to choose individuals for reproduction. Crossover operations recombine genetic material, while mutation introduces diversity to help avoid premature convergence. This process repeats until convergence is achieved or a predefined number of generations is reached.

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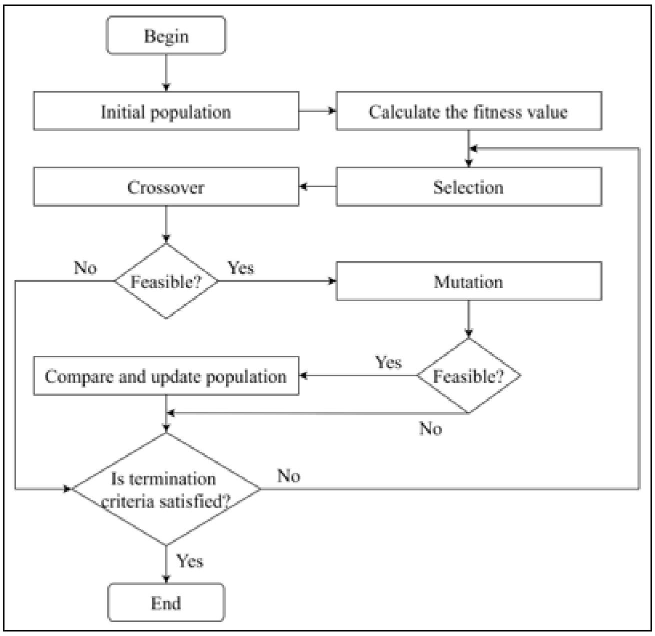

Figure 2: The flow chart of genetic algorithm

4. Experimental Design

4.1 Case study

To support this study, a comprehensive field survey was conducted at the Blood Preparation and Distribution Department of Hospital X. The aim was to collect detailed information on the organizational structure, operational practices, shift arrangements, and task execution, which serves as the basis for developing a realistic and practical scheduling model.

The department is structured with a Head who oversees all activities, supported by a Deputy Head responsible for assisting in management and supervision. A Chief Technician is tasked with assigning daily work schedules, while an Accounting Officer manages administrative reports, including blood inventory and CPM system records. The Quality Management team includes two staff members: one focuses solely on paperwork and process oversight, while the other combines documentation with technical responsibilities. The core workforce consists of 25 professional staff members assigned to various operational tasks such as Receiving, Preparation, Evaluation and Labelling, Distribution, and Transport.

To ensure uninterrupted service for patients, the department operates 24/7. Regular staff follow two main shifts: Shift 1 runs from 7:30 AM to 4:30 PM, and Shift 2 from 10:00 AM to 7:00 PM. Radiation staff also follow two shifts with slightly different timing: 8:00 AM to 4:30 PM for Shift 1 and 11:00 AM to 7:00 PM for Shift 2. Distribution staff follow 24-hour shifts, typically from 7:30 AM on one day to 7:30 AM the next.

Workforce assignments vary by task. In Receiving and Preparation, about 12 employees are scheduled daily across two shifts, with 7 – 8 in Shift 1 and 4 – 5 in Shift 2. Two staff members are also assigned to 24-hour duty shifts for irradiation tasks. In the Evaluation and Labelling unit, around four employees are needed daily. The Distribution team includes one administrative staff working five days per week and two staff (one radiation, one regular) assigned to 24-hour duty on a rotational basis. Radiation staff are scheduled once every seven days, and regular staff once every fifteen days. Employees on 24-hour duty receive a compensatory day off. If a staff member is unexpectedly absent, the following shift's duty staff take over, or duty assignments are adjusted based on availability.

Transportation tasks occur on specific days: Monday, Wednesday, and Friday (both morning and afternoon) and Tuesday, Thursday, and Saturday (morning only). Two staff members accompany the blood truck per session, assigned on a rotating basis. As only one truck is available and used based on actual demand, staff not involved in transport at a given time may be reassigned to support other departments.

The figure 3 shows the weekly master plan and staffing allocation template and figure 4 shows the example of weekly master plan and staffing allocation.

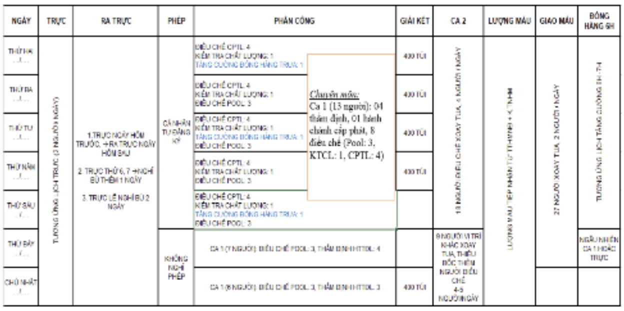

Figure 3: Weekly master plan and staffing allocation template

Figure 4: Example of weekly master plan and staffing at blood bank

4.2 Computational results

This research paper aims to address the case study at Hospital X using Mixed-Integer Linear Programming and Genetic Algorithm approaches. The case study dataset in current system is presented in the Table 2.

The MILP model will be solved on an ASUS Core i5-8250U CPU (8 CPUs), 8GB RAM personal computer with IBM ILOG CPLEX Optimization Studio Version 12.9.0. Subsequently, the problem will be addressed using the GA method, implemented in Python. To ensure a robust comparison, the GA method will be executed multiple times, and both the average and best-performing solutions will be analyzed against the MILP solution.

Table 2: Dataset of case study at Hospital X in current system

Number of Radiation staff	Number of Regular staff	Number of Admin	J	S	D	W
17	8	2	9	8	7	4

We first solve the sub-model to identify potential infeasibility in the primary model. Assuming no overtime (F^{max} = 90, or 45 hours/week), the model indicates that Hospital X would need 34 staff, up from the current 27 – an impractical increase due to resource constraints. Therefore, staff overtime is necessary to meet operational demands.

Vietnamese labor law allows up to 200 hours of overtime per year (about 4 hours/week), so F^{max} is adjusted to 98. Under this constraint, the sub-model shows that hiring five additional employees would ensure compliance – a feasible solution given manageable cost.

Alternatively, removing weekly working hour limits and keeping the current workforce size, the model shows that 30 employees are needed: 1 administrative, 20 radiation, and 9 regular staff. In reality, Hospital X has only 17 radiation staff, 8 regular staff, and 2 administrative staff – highlighting a workforce shortage that leads to schedule imbalance.

To resolve this, input data will be refined to better match constraints, and optimal or feasible schedules will be generated using CPLEX and Genetic Algorithm.

Table 3: Dataset of case study at Hospital X

Number of Radiation staff	Number of Regular staff	Number of Admin	J	S	D	W
20	9	1	9	8	7	4

After adjusting the input data, we rerun the CPLEX program to seek an optimal solution before applying the GA algorithm. However, due to the dataset's size and limited computing resources, CPLEX failed to find an optimal solution. As a result, we have imposed a thirty-minute runtime limit on CPLEX to evaluate its output against the sample schedule from Hospital X.

Table 4: The technical parameters for Genetic Algorithms for solving real case problem

Population size	Selection size	Mutation rate	Number of generations
20	3	10%	200

The GA produced a result with a solving time of approximately 400 seconds. When directly compared to the solution from the MILP model, this result is relatively poor. Despite multiple attempts, the solution quality could not be improved. One possible reason for this suboptimal performance is the mutation method used. The current mutation approach only makes small structural changes within a vast solution space, causing the algorithm to get stuck in a local optimum without significant improvements. However, we will still compare the results from this algorithm with the actual situation to assess its practical usefulness.

Table 5: Computation time and performance

	Current system	MILP (600s)	MILP (1800s)	GA
Number of regular – radiation staff	17 – 8	20 – 9	20 – 9	20 – 9
Obj.	29,040	22,153	22,153	~ 28,000
Biggest gap between staff (hour/week)	60	50	50	50
Run time	-	600 s	1800s	~ 250s

Although the solution of GA is not good as the one was given by MILP, it is still better than the current system. The gap between the staff working most in the week and the staff working less in week has gone down. However, this solution can be considered as a temporary solution for Hospital X as the solution is for 30 employees in total, while the total number of employees at hospital X is only 27.

5. Conclusion, implications and recommendations

This case study presents a practical solution for workforce scheduling in blood production, applying MILP and GA methodologies to balance workloads and minimize overtime. While the MILP model achieved better performance, the GA approach provides a faster, albeit suboptimal, alternative for real-world application. The research underscores the need for adaptable scheduling tools in healthcare logistics, especially under resource constraints. Future work should focus on enhancing algorithmic performance and integrating predictive models for demand forecasting to further optimize staffing decisions.

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