

Integer Linear Programming Models for Preventive Maintenance of Medical Devices: A Case Study

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Abstract

This study aims to develop a mathematical decision-support framework for optimizing workforce allocation and operational planning in medical device preventive maintenance (PM). An investigation a case study at a public hospital revealed that the PM plan for medical devices at the operational level often lacks decision-support tools for effective work planning. Due to the large number and diverse range of medical devices in hospitals, the head of the medical device department often encounters difficulties in allocating technicians efficiently across different device categories according to their skill levels and time constraints. This limitation frequently results in disproportionate workloads and an inequitable distribution of tasks among personnel. To address these inefficiencies, this study employs a sequential optimization framework consisting of a Binary Integer Linear Programming (BILP) model followed by an Integer Linear Programming (ILP) model. First, the BILP model assigns maintenance tasks based on technician skills and time constraints with the simultaneous optimization of workload balance and equitable distribution of maintenance tasks among technicians within a single model. The optimized BILP output is then used as input for the ILP model to determine optimal daily task allocation. This sequential approach effectively reduces computational complexity. The proposed models are implemented within Microsoft Excel and integrated with OpenSolver, a free and open-source optimization solver, to provide a flexible and cost-effective alternative to manual planning. The results indicate that the proposed BILP and ILP models reduced labor costs by 12.64% and 12.60%, respectively, compared with the current maintenance planning. The proposed model effectively balances workloads among technicians within the same skill group, resulting in workload deviations of 0.70% and 0.84% for the skilled and general groups, respectively. Furthermore, equitable task distribution is achieved, as the difference in the number of assigned devices of each type among technicians within the same skill group does not exceed one device.

Keywords: Workforce allocation, Operational planning, Spreadsheet-based optimization, Binary integer linear programming

1. Introduction

Medical devices are instruments that assist healthcare professionals in diagnosing, treating, or curing illnesses more efficiently. Frequent malfunctions or breakdowns during use can reduce user confidence in the device and lead to safety concerns for patients receiving care. Proper maintenance of medical devices to prevent premature failures and to ensure that the device remains in functional condition enhances patients' confidence and sense of safety while receiving medical services. It also helps reduce operational costs while improving overall operational efficiency. Delays in maintenance activities worsen the condition of the device, resulting in longer repair times required to restore devices to their normal state [1]. Effective medical device maintenance is critical to ensuring the availability, precision, and accuracy of medical devices used in healthcare services. The maintenance of medical device in hospitals involves three principal processes, namely Testing and Commissioning (T&C), Inspection and Preventive Maintenance (IPM), and Corrective Maintenance (CM), which collectively ensure the reliability and safety of medical devices [2]. To optimize IPM implementation, the Medical Engineering Division (MED), Ramathibodi Facilities Services (RFS), and the Emergency Care Research Institute (ECRI) stated that the determination of maintenance intervals for medical devices in the IPM work plan should be determined in accordance with the manufacturer's recommendations and

by considering the following factors including 1) the age of the device, 2) the frequency of device usage, 3) the history of device failures, 4) the risk level of the device, 5) the number and expertise of technicians in the medical device department, and 6) the level of training programs provided to users and technicians [2]. The planning and allocation of technicians for preventive maintenance activities represent a complex decision-making problem, particularly under constraints related to budget, operational time, and limited workforce availability. Workload balancing focuses on distributing tasks in alignment with personnel capabilities, skills, and operational capacities to optimize resource utilization. Concurrently, fairness management emphasizes the equitable distribution of work among technicians. Consequently, a balanced workload schedule may not always reflect fairness, and conversely, an equitable allocation of tasks may not result in a perfectly balanced workload. Due to the large number and diverse range of medical devices in hospitals, the head of the medical device department often encounters difficulties in allocating technicians efficiently across different device categories according to their skill levels, while simultaneously ensuring workload balance and equitable distribution of maintenance tasks among technicians. Therefore, mathematical optimization techniques have been increasingly employed to support maintenance workforce allocation and operational planning. Despite their effectiveness, the adoption of

commercial workforce scheduling software is often constrained by limited financial resources in hospitals. Consequently, spreadsheet-based optimization has gained increasing attention as a cost-effective decision-support approach for maintenance workforce planning and scheduling. By implementing an Integer Linear Programming (ILP) model within a spreadsheet environment such as Microsoft Excel and integrating it with a non-commercial optimization solver such as OpenSolver, the proposed framework integrates data management, analysis, and optimization within a single platform. This approach eliminates the need for expensive workforce scheduling software and extensive programming expertise while maintaining the capability to generate high-quality, near-optimal solutions. Furthermore, the ILP-based framework enables medical device department heads, as end users, to efficiently generate workforce allocation plans and detailed daily schedules for preventive maintenance activities. The framework ensures that maintenance tasks are completed within available resource, budget, and time constraints while promoting workload balance and equitable distribution of maintenance tasks among technicians, thereby improving operational efficiency and workforce utilization.

2. Literature Review

Maintenance optimization studies generally classify maintenance planning and scheduling into two main categories: 1) scheduled maintenance and 2) unscheduled maintenance. Scheduled maintenance includes 1.1) preventive and routine maintenance and 1.2) planned overhauls and corrective maintenance. In contrast, unscheduled maintenance involves emergency breakdowns and is inherently stochastic in nature [3].

Wagner et al. [4] introduced mathematical programming approaches for preventive maintenance scheduling using ILP models. Their work demonstrated that optimization techniques could effectively support manpower allocation and maintenance scheduling decisions. Manzini [3] developed a Mixed Integer Linear Programming (MILP) model to optimize preventive maintenance scheduling for complex packaging machines. In addition, MILP frameworks have been widely applied to workforce allocation and maintenance scheduling across various industries. For example, in offshore wind farms, Tusar and Sarker [5] developed a MILP model to optimize the assignment of technicians to maintenance shifts, aiming to minimize unmet maintenance demand while ensuring a balanced workload among technicians. Similarly, in high-speed railway systems, Zhang et al. [6] proposed a MILP model to support operational-level maintenance planning by integrating overnight train scheduling with maintenance task scheduling, thereby enhancing the coordination between railway operations and maintenance activities. In the electric power utility sector, Delgadillo et al. [7] also proposed a MILP model to optimize the allocation of technicians considering factors such as capacity, availability, priority of service orders, and waiting times. In international Breweries sector, Micheal

and Ikechi [8] developed Binary Integer Linear Programming (BILP) model to determine the optimal allocation of personnel to work shifts while satisfying operational, regulatory, and skill requirements. These studies demonstrate the effectiveness of mathematical optimization techniques for addressing complex maintenance scheduling and workforce allocation problems.

In parallel, spreadsheet-based optimization has emerged as a practical and accessible approach for supporting operational planning and scheduling. The spreadsheet-based optimization models integrated with optimization add-ins such as Premium Solver Platform and OpenSolver, can effectively formulate and solve Integer Programming problems, including workforce allocation and operational planning. These tools are widely adopted due to their flexibility, ease of use, and ability to integrate data management, analysis, and optimization within a single platform. Artana and Ishida [9] developed and used a spreadsheet model to determine the optimum maintenance schedule for ship machinery. Nonlinear Integer programming (NLIP) model was formulated for the problem and using Premium Solver Platform to determine the optimal maintenance interval and frequency. Ovchinnikov and Milner [10] developed a spreadsheet-based optimization model to support the complex task of assigning 15 medical residents to a full year of on-call and emergency room (ER) shifts. The scheduling problem was formulated as a BILP model with approximately 10,000 decision variables representing resident assignments to on-call and ER duties on a given day. The model was implemented in Microsoft Excel and solved using the XPRESS Solver Engine. Zheng and Gong [11] demonstrated that spreadsheet-based optimization can effectively support workforce scheduling. By integrating an ILP model with a Variable Neighborhood Search (VNS) algorithm implemented in VBA within Microsoft Excel, the proposed system generated high-quality nurse rosters while ensuring continuity of care and fairness in nurse assignments. Smalley and Keskinocak [12] developed IP models to support resident physician scheduling in academic teaching hospitals. The models optimized annual rotation assignments and call-shift scheduling while satisfying educational requirements, duty-hour regulations, and operational constraints. To ensure fairness and equivalent training opportunities, balancing constraints were incorporated to distribute rotation experiences among residents. The results demonstrated that the optimization approach improved schedule quality, reduced manual scheduling effort, and effectively supported workforce allocation under complex scheduling requirements. Anderson et al. [13] developed a spreadsheet-based nurse scheduling tool based on a sequential Integer Programming approach to address workforce allocation in long-term care facilities. The two MILP models was proposed for nurse scheduling. The first model focused on maximizing demand coverage, whereas the second model optimized employee preferences based on the demand level obtained from the first model. This hierarchical solution strategy enabled the scheduling

process to prioritize critical operational requirements before considering workforce preferences, thereby balancing service demand fulfillment and employee satisfaction. The proposed approach generated near-optimal solutions using OpenSolver within a reasonable computational time. Healthcare facilities rely heavily on medical device to provide effective patient care. The increasing complexity and quantity of medical devices have led to significant challenges in maintenance management. Preventive maintenance management for medical device can be divided into three levels: strategic [14–15], tactical [16], and operational [17–18]. This research addresses workforce planning at the operational level of preventive maintenance management.

Previous studies have demonstrated the effectiveness of optimization models for workforce allocation and operational planning across various application domains. In particular, spreadsheet-based optimization models have been widely adopted because they provide a flexible and cost-effective platform for formulating and solving optimization problems. An overview of the relevant literature is presented in **Table 1**. However, the existing literature on workforce allocation has primarily focused on operational efficiency and resource utilization, with limited attention to the simultaneous consideration of workload balance and equitable distribution among workers. Most studies (**Table 1**) have considered only one of these aspects or have overlooked both dimensions

altogether. Consequently, there remains a research gap in developing workforce allocation model that simultaneously consider workload balance and equitable distribution in a single optimization model. Furthermore, the literature has not yet reported the application of spreadsheet-based optimization models to workforce allocation and operational planning in preventive maintenance of medical devices.

To address these gaps, this research develops two ILP models implemented within a spreadsheet environment to optimize workforce allocation and operational planning for medical device preventive maintenance. The first BILP model optimizes workforce allocation by incorporating technician skill levels, time constraints, workload balance, and equitable distribution among technicians. The second ILP model then optimizes operational planning based on the allocation plan generated by the first model.

The primary contribution of this paper is the development of ILP models, which simultaneously address workload balance, equitable distribution, and operational planning in medical device preventive maintenance. Furthermore, these models are implemented within Microsoft Excel and integrated with OpenSolver, a free and open-source optimization solver. By utilizing a single and cost-effective platform, the proposed approach provides a practical and highly accessible solution for organizations that cannot afford specialized scheduling software.

Table 1 Summary table of previous studies focused on spreadsheet-based optimization models

Publication	Applications	Planning stage	IP model	Workload balance	Equitable distribution	Solver software
Artana and Ishida [9]	Ship machinery	Tactical level	NLIP	No	No	Premium Solver Platform
Ovchinnikov and Milner [10]	Medical residents	Operational level	BILP	Yes	No	XPRESS Solver Engine
Zheng and Gong [11]	Nurse rostering	Operational level	ILP	No	Yes	VBA-based VNS in MS Excel
Smalley and Keskinocak [12]	Medical residents	Tactical level	1-MILP	Yes	No	Cplex
		Operational level	2-MILP			
Anderson et al. [13]	Nurse rostering	Operational level	1-MILP	Yes	No	OpenSolver
			2-MILP			
This paper	Medical devices	Operational level	1-BILP	Yes	Yes	OpenSolver
			2-ILP			

3. Problem Description

Preventive maintenance management for medical device aims to reduce long-term maintenance costs and minimize downtime without impacting the availability of medical device [19]. The medical device department of the case study hospital is responsible for maintaining medical devices to ensure the safety of patients, healthcare service users, and medical personnel. Malfunctioning or inadequately maintained medical devices may pose significant risks to patient care and user safety. One of the primary responsibilities of the department head is to develop preventive maintenance plans and assign maintenance tasks to technicians according to their skill levels. Preventive maintenance activities are performed on

out-of-warranty medical devices (in-house service) during both regular working hours and overtime periods throughout each fiscal year. The maintenance workforce consists of two groups of technicians: 1) skilled technicians and 2) general technicians. Skilled technicians are qualified to perform preventive maintenance on all types of medical devices, whereas general technicians are authorized to maintain only devices requiring low-level technical skills. The preventive maintenance tasks are classified into three skill levels. Level 1 involves basic inspection and servicing activities, such as checking cables and batteries, disassembling components, and cleaning the device. Level 2 includes installing and configuring calibration equipment, performing calibration procedures,

reading measurement values, and recording the results. Level 3 comprises advanced maintenance activities, including verifying the correctness of calibration system connections, adjusting device parameters to meet operational standards, interpreting measurement results, and documenting, analyzing, and summarizing maintenance outcomes.

External vendors are responsible for maintaining medical device under warranty or with technical service contracts. Currently, preventive maintenance planning for medical devices is performed manually by the department head. The existing maintenance plan specifies only maintenance dates and assigned technicians, without providing detailed information regarding the specific devices and quantities assigned to each technician. In addition to PM activities, technicians are required to perform routine repair and corrective maintenance tasks on a daily basis. Consequently, PM activities are frequently postponed until the latter part of the planning horizon. Moreover, technicians typically perform maintenance tasks without considering the urgency of approaching deadlines. As a result, maintenance activities tend to accumulate near the deadline, leading to excessive and often unnecessary overtime work.

Another limitation of the current planning approach is the imbalance in workload distribution among technicians within the same skill group. Significant differences are observed in both the total maintenance time assigned to technicians and the number of maintenance tasks involving the same type of medical device. Such disparities result in an unfair workload distribution among both skilled and general technicians. Furthermore, technicians are responsible for a variety of additional duties, including building maintenance, electrical and plumbing work, and providing consultations on medical device usage. As individual technicians have limited visibility of their overall workload across the entire planning horizon, effective workforce allocation and daily operational planning become complex. To overcome these limitations, a mathematical optimization model was developed to support workforce allocation and maintenance task assignment according to technician skill levels. The model incorporates workload-balancing constraints and the department head's requirements regarding maintenance completion within the specified planning horizon. This study investigates the problem of allocating technical personnel for preventive maintenance activities in hospital medical devices with the objective of improving maintenance efficiency, enhancing workload fairness, and increasing resource utilization.

4. Mathematical Model

Currently, department staff manually coordinate maintenance tasks for medical devices. This manual system lacked crucial information, such as the specific type and quantity of devices assigned to individual technicians, and resulted in disproportionate workload distribution among skilled personnel. To address these inefficiencies, a decision-support tool was developed to optimize workforce allocation and daily operational

planning using two mathematical models: 1) BILP and 2) ILP. The first model (BILP) assigns tasks to technicians, specifying the designated clinical departments and devices for both regular and overtime hours. This allocation strictly adheres to skill levels and temporal constraints to ensure completion within established deadlines. The optimized output from the BILP model subsequently serves as the input parameter for the second model (ILP) to determine the optimal daily operational planning for each technician. This sequential approach significantly reduces computational complexity and improves solution efficiency.

4.1 Mathematical Model for Workforce Allocation (BILP)

4.1.1 Assumptions

1) The time required for maintenance is standardized by device type, assuming that technicians spend equal time on similar device regardless of the brand.

2) The age of the medical device is assumed to have no impact on the preventive maintenance duration; specifically, the time required for maintenance remains constant for both new and aging equipment.

3) Each preventive maintenance task is indivisible and must be performed and completed by a single technician within the same operational day, either during regular working hours or during overtime.

4.1.2 Sets

- I Set of technicians, $I = \{1, 2, 3, \dots, i\}$
- I_j^a Skilled technicians working on the device j ,
 $I_j^a \subset I$
- I_j^b General technicians working on the device j ,
 $I_j^b \subset I$
- J Set of devices, $J = \{1, 2, 3, \dots, j\}$
- J^L Set of devices maintained by technicians, $J^L \subset J$
- J^H Set of devices maintained by skilled technicians, $J^H \subset J$
- M Set of clinical departments, $M = \{1, 2, 3, \dots, m\}$
- T Technician working hours, $T = \{1: \text{Regular-time}, 2: \text{Overtime}\}$

4.1.3 Parameters

- A_{jm}^t Total number of devices of type j in clinical department m that requires maintenance during period t
- C_i^t The labor cost for technician i to work during period t (baht/minutes)
- D The difference in total operational hours between each technician (minutes)
- P_{ij} Time technician i performs on device j (minutes)
- S_i^t Total time assigned by the medical device department head for technician i to work during period t (minutes)

4.1.4 Decision Variables

$X_{ijm}^t = 1$ when technician i performs work on device j in department m during period t . Otherwise, it is 0.

4.1.5 Objective Function

The objective function aims to minimize total labor cost, including both regular-time and overtime labor costs, by optimally allocating the workforce to maintenance tasks. This ensures that all maintenance activities are completed within the designated planning horizon as shown in Eq. (1)

$$\text{Min } \sum_i \sum_j \sum_m \sum_t P_{ij} C_i^t X_{ijm}^t \quad (1)$$

4.1.6 Constraints

1) The total working time for each technician within the specified timeframe must not exceed the total working time that the head of the medical device department has determined for each technician, including both regular and overtime hours. This is shown by Eq. (2).

$$\sum_j \sum_m P_{ij} X_{ijm}^t \leq S_i^t, \forall i, t \quad (2)$$

2) All devices of each type j in each clinical department m that require maintenance must be assigned to technicians as shown as Eq. (3).

$$\sum_i \sum_t X_{ijm}^t = A_{jm}, \forall j, m \quad (3)$$

3) ensure workload fairness, the difference in the number of maintenance tasks involving the same type of medical device assigned to any two technicians is restricted to no more than one device, as formulated in Eq. (4) for general technicians and Eq. (5) for skilled technicians.

$$\sum_m X_{ijm}^t - \sum_m X_{hjm}^t \leq 1, \text{ for } h \neq i, i \in I_j^b, i \in I_j^b, \forall j, t \quad (4)$$

$$\sum_m X_{ijm}^t - \sum_m X_{gjm}^t \leq 1, \text{ for } g \neq i, i \in I_j^a, i \in I_j^a, \forall j, t \quad (5)$$

4) Workloads are balanced within each set of technicians. This is shown by Eqs. (6)–(9). To ensure a balanced workload among technicians, the difference in total operational hours between any pair of technicians is constrained not to exceed a specified limit. This requirement is formulated in Eqs. (6)–(7) for general technicians and Eqs. (8)–(9) for skilled technicians.

$$\sum_j \sum_m P_{ij} X_{ijm}^t - \sum_j \sum_m P_{ij} X_{hjm}^t \leq D, \text{ for } h \neq i, i \in I_j^b, i \in I_j^b, \forall t \quad (6)$$

$$\sum_j \sum_m P_{ij} X_{hjm}^t - \sum_j \sum_m P_{ij} X_{ijm}^t \leq D, \text{ for } h \neq i, i \in I_j^b, i \in I_j^b, \forall t \quad (7)$$

$$\sum_j \sum_m P_{ij} X_{ijm}^t - \sum_j \sum_m P_{ij} X_{gjm}^t \leq D, \text{ for } g \neq i, i \in I_j^a, i \in I_j^a, \forall t \quad (8)$$

$$\sum_j \sum_m P_{ij} X_{gjm}^t - \sum_j \sum_m P_{ij} X_{ijm}^t \leq D, \text{ for } g \neq i, i \in I_j^a, i \in I_j^a, \forall t \quad (9)$$

5) General technicians cannot perform work on medical device that requires high skill levels. This is shown by Eq. (10).

$$X_{ijm}^t = 0, \forall i \in I_j^b, \forall j \in J^H, \forall m, t \quad (10)$$

6) All decision variables are binary variables as follows Eq. (11).

$$X_{ijm}^t \in \{0,1\}, \forall i, j, m, t \quad (11)$$

4.2 Mathematical Model for Daily Operational Planning (ILP)

4.2.1 Assumptions

1) The accumulated operating time of a medical device does not influence the duration required for technicians to perform preventive maintenance.

4.2.2 Sets

- J Set of devices, $J = \{1, 2, 3, \dots, j\}$
- M Set of clinical departments, $M = \{1, 2, 3, \dots, m\}$
- T Technician's working hours, $T = \{1: \text{Regular hours}, 2: \text{Overtime}\}$
- W Technician's working days,

4.2.3 Parameters

- P_j Standard time that technicians perform at device j (minutes)
- R_j Operational risk cost associated with device j (baht/unit)
- Cap_w^t Time period assigned by the medical device department head for technicians to perform work during workday w at time period t (minutes)
- X_{ijm}^t Number of medical devices allocated to technicians for maintenance at department m on device j during time period t (devices)

4.2.4 Decision Variable

- Y_{jmw}^t Number of medical devices that technicians must work on at department m on device j during time period t of workday w

4.2.5 Objective Function

This model aims to develop a daily operational plan for technicians that ensures preventive maintenance tasks are completed within the required time frame while minimizing operational risk cost. Operational risk cost is a time-dependent cost that reflects the increasing risk of medical equipment failure when preventive maintenance is delayed. The longer the delay, the greater the likelihood of equipment malfunction during service, which may lead to operational disruptions, safety hazards, and adverse impacts on patients and healthcare providers as shown in Eq. (12).

$$\text{Min } \sum_j \sum_m \sum_t \sum_w R_j Y_{jmw}^t \quad (12)$$

4.2.6 Constraints

1) The number of hours each technician is allocated to perform maintenance work during period t on each working day w must not exceed the number of hours determined by the head of medical equipment department, i.e., regular working hours and overtime (minutes per day) as shown in Eq. (13).

$$\sum_j \sum_m P_j Y_{jmw}^t \leq Cap_w^t, \forall t, w \quad (13)$$

2) To ensure consistency between models, the cumulative daily assignments in the second model must satisfy the optimal workload allocation obtained from the initial optimization phase as shown in Eq. (14).

$$\sum_w Y_{jmw}^t = X_{jm}^t, \forall j, m, t \quad (14)$$

3) All decision variables must be positive integers, as shown in Eq. (15).

$$Y_{jmw}^t \geq 0 \text{ and integer, } \forall j, m, t, w \quad (15)$$

5. Research Results

5.1 Mathematical Model for Workforce Allocation (BILP)

5.1.1 Illustrative Case Study

Data were collected from medical device records provided by the department head, focusing on devices

requiring preventive maintenance under a 12-month maintenance cycle. These data served as input for validating the proposed BILP model. The maintenance team comprised two skilled technicians (A and B) and two general technicians (C and D), as detailed in **Table 2**. A total of 430 medical devices located across 20 clinical departments were scheduled for preventive maintenance within a 30-day planning horizon. Based on the technical expertise required, the devices were categorized into two skill groups: a low-skill group consisting of device types 1 and 2, and a high-skill group consisting of device types 3, 4, and 5. Overtime work on weekdays was permitted to ensure that all maintenance tasks could be completed within the planning horizon. The standard preventive maintenance times for each device type are provided in **Table 3**.

Table 2 Personnel information of technicians

No.	Position	Skill level
1	Skilled technician (A,B)	High: 3
2	Technician (C,D)	Low: 1,2

Table 3 Classification of medical device characteristics by required technician skill level

Type no.	Device name	Skill level	Standard time (min.)	Number of devices	Time spent (min.)
1	Blood pressure monitor	1,2	50	194	9,700
2	Oxygen saturation monitor		45	48	2,160
3	Electrocardiogram (ECG)	1,3	45	11	495
4	Air-oxygen mixer		55	15	825
5	Automatic infusion pump		80	162	12,960
Total				430	26,140

The head of the medical device department was responsible for planning and allocating a total of 430 medical devices of preventive maintenance work among four technicians, technicians A and B, who are highly skilled technicians. technicians C and D, who are general technicians. The assigned workload could be performed during both regular working hours and overtime, subject to a maximum of 4 regular hours and 1.5 overtime hours per technician per day. All maintenance tasks were required to be completed within a 30-working-day planning horizon.

The BILP model was implemented in a Microsoft Excel spreadsheet and solved using OpenSolver 2.9.4 [8], an Excel add-in that supports linear and integer programming within the Excel environment. The optimization results, generated on a laptop computer with an Intel Core i5 2.11 GHz processor, 16 GB RAM, and Windows 10 Pro, are summarized in **Table 4**. The results indicate that the difference in the number of devices assigned between skilled technicians A and B and between technicians C and D is only one device. This result satisfies the workload-balancing constraint specified in Eqs. (6)–(9).

Table 4 Optimal assignment of technicians to maintenance tasks in the base-case scenario

Technician	Device type					Total	Time used (Min.)
	1	2	3	4	5		
A	-	-	6	8	81	95	7,190
B	1	-	5	7	81	94	7,140
C	97	24	-	-	-	121	5,930
D	96	24	-	-	-	120	5,880
total	194	48	11	15	162	430	26,140

5.1.2 BILP Model Validation

Under the current situation, preventive maintenance planning is conducted on an ad-hoc basis, whereby technicians are assigned to complete all due maintenance tasks within the 30-day period. However, technicians must also perform routine repair and corrective maintenance activities on a daily basis. As a result, preventive maintenance tasks are often postponed until the latter part of the planning horizon. This leads to a concentration of workload near the deadline and increases the reliance on overtime work to ensure task completion. To compare the labor cost efficiency of the current planning practice with that of the optimal plan generated by the Binary Integer Linear Programming (BILP) model, the current planning scenario was

evaluated using the same mathematical model. However, the model parameters were adjusted to reflect the actual working pattern of technicians under the existing planning approach described above. The solutions obtained using OpenSolver [20] under the current planning practice and the optimal BILP-based planning approach are shown in the rows labeled “Be.” (Before) and “Af.” (After), respectively, as illustrated in **Table 5** which provides sample optimal solution outputs for 8 clinical departments. According to the optimal BILP-

based planning solution, all maintenance tasks can be completed within the available regular working hours, with no overtime required as illustrated in **Table 6**. Technicians C and D were assigned only device types 1 and 2, totaling 241 units, whereas skilled technicians A and B were assigned on all equipment units, particularly device items 3, 4, and 5. Technicians C and D, however, were unable to handle these devices, which aligns with the constraints defined in the BILP model as shown in **Table 6**.

Table 5 Illustrative results of the base-case scenario before and after applying the BILP solution

Department		Device type (Reg./OT)																		Total		
		Technician (C)				Technician (D)				Skilled technician (A)					Skilled technician (B)							
		1	OT	2	OT	1	OT	2	OT	3	OT	4	OT	5	OT	3	OT	4	OT		5	OT
1	Be.	-	-	-	-	6	1	-	2	-	-	3	-	-	3	-	-	1	-	2	3	21
	Af.	-	-	-	-	9	-	-	-	1	-	1	-	10	-	-	-	-	-	-	21	
2	Be.	-	2	2	2	-	-	-	-	2	1	3	-	5	1	-	-	-	-	-	18	
	Af.	6	-	-	-	-	-	-	-	1	-	-	-	10	-	-	-	1	-	-	18	
3	Be.	-	-	-	-	5	1	-	4	-	-	-	-	-	-	-	-	-	-	6	16	
	Af.	-	-	-	-	6	-	4	-	-	-	-	-	-	-	-	-	1	-	5	16	
4	Be.	-	-	-	-	5	-	-	2	-	-	-	-	9	1	-	-	-	-	-	17	
	Af.	-	-	-	-	9	-	-	-	-	-	1	-	5	-	2	-	-	-	-	17	
5	Be.	-	-	-	-	-	3	-	2	2	-	2	-	8	-	-	-	-	-	-	17	
	Af.	-	-	-	-	5	-	-	-	-	-	-	-	12	-	-	-	-	-	-	17	
6	Be.	9	1	-	2	-	-	-	-	-	-	-	-	3	5	-	-	-	-	-	20	
	Af.	8	-	4	-	-	-	-	-	-	-	-	-	7	-	-	-	1	-	-	20	
19	Be.	12	2	-	2	-	4	-	-	-	-	-	-	-	-	-	-	-	-	-	20	
	Af.	16	-	-	-	-	-	4	-	-	-	-	-	-	-	-	-	-	-	-	20	
20	Be.	14	1	-	1	-	-	-	-	-	-	-	1	1	2	-	-	-	-	-	20	
	Af.	12	-	-	-	-	-	4	-	-	-	-	-	4	-	-	-	-	-	-	20	

Table 6 Maintenance task allocation before and after applying the BILP solution (base-case scenario)

Technician		Device type (Reg./OT)									
		1	OT	2	OT	3	OT	4	OT	5	OT
A	Be.	1	1	-	-	5	4	11	3	55	19
	Af.	-	-	-	-	6	-	8	-	81	-
B	Be.	-	-	-	-	2	-	1	-	61	27
	Af.	1	-	-	-	5	-	7	-	81	-
C	Be.	86	16	4	24	-	-	-	-	-	-
	Af.	97	-	24	-	-	-	-	-	-	-
D	Be.	76	14	-	20	-	-	-	-	-	-
	Af.	96	-	24	-	-	-	-	-	-	-
Total	Be.	163	31	4	44	7	4	12	3	116	46
	Af.	194	-	48	-	11	-	15	-	162	-

The proposed ILP models were solved using the CBC solver available through OpenSolver. CBC (COIN-OR Branch-and-Cut) solver employs a branch-

and-bound framework combined with cutting-plane methods to obtain optimal solutions for MILP problems [21]. The B&B algorithm continues until

one of the following termination criteria is met: all unexplored nodes are explored, the optimality gap is closed (i.e., the primal bound of an integer feasible solution matches the dual bound), or a specified computational limit (such as a timeout) is exceeded [22]. For a minimization problem, the primal bound (i.e., the upper bound) corresponds to the objective value of the best incumbent feasible solution, whereas the dual bound represents the lower bound on the optimal objective value. The relative optimality gap (hereafter referred to as the optimality gap) is calculated as follows: the optimality gap = $1 - [\text{best lower bound}/\text{best current solution}]$ [23]. Rather than requiring proof of global optimality, Gurobi, a commercial MIP solver, considers a solution to be optimal when the relative optimality gap falls below its default tolerance of 0.0001 (0.01%) [23]. Moreover, near-optimal solutions with relative optimality gaps ranging from 1% to 10% are often deemed acceptable, as they provide a favorable trade-off between solution quality and computational time [24]. The computational efficiency of the proposed model was measured using CPU time to reflect computational complexity, and the optimality gap to determine the accuracy of the final solution. These results of the BILP model were shown in **Table 7**. The proposed BILP model was solved efficiently, requiring only 0.2 CPU seconds to obtain a solution. The optimality gap was 0.04%, which is substantially lower than the commonly accepted threshold of 1% for near-optimal solutions. The results show that the workload is balanced among technicians within the same skill group, with the difference in the number of assigned devices of each type not exceeding one device. Furthermore, no overtime work is required. The proposed BILP model reduced labor costs by 12.64% compared with the current maintenance planning practice while ensuring that all preventive maintenance tasks were completed within the planning horizon.

Table 7 Comparison of cost and computational performance before and after applying the BILP solution in the base-case scenario

The base case scenario	Before	After
Time (CPU seconds)	0.09	0.2
Regular labor cost	17,634.40	24,768.75
Overtime labor cost	10,717.20	-
Objective function cost	28,351.60	24,768.75
Lower bound	28,351.6	24,758.33
Optimality gap	0.00%	0.04%

5.1.3 Performance Evaluation of the BILP Model

The computational performance of the proposed BILP model was evaluated under different problem sizes by considering three planning scenarios with increasing numbers of medical devices. The base-case scenario included 430 devices and 3,440 decision variables. Scenario 1.0 increased the number of

devices to 659, resulting in 5,272 decision variables, while Scenario 2 doubled the number of devices relative to the base case, yielding 860 devices and 6,880 decision variables. Computational performance was assessed in terms of the number of decision variables, CPU time, and optimality gap. In the base-case scenario, Technicians A, B, C, and D were available for up to 4 regular working hours and 1.5 overtime hours per day. To accommodate the increased workload in scenarios 1 and 2, the overtime allowance was increased to 3 hours per day while maintaining 4 regular working hours per day for each technician. All maintenance activities were scheduled within a 45-day planning horizon. The characteristics of the three scenarios are presented in **Table 8**.

Table 8 Scenario settings for the preventive maintenance planning problem

Scenario	Base case		1.0		2	
No. of devices	430		659		860	
No. of variables	3,440		5,272		6,880	
Planning horizon	30	30	45	45	45	45
Hrs./day	Reg	OT	Reg	OT	Reg	OT
A	4	1.5	4	3	4	3
B	4	1.5	4	3	4	3
C	4	1.5	4	3	4	3
D	4	1.5	4	3	4	3

The solutions obtained for all three scenarios, as presented in **Table 9**, required less than 0.65 seconds of CPU time, while the optimality gap remained below 0.08% in every case. These results indicate that the solutions can be considered near-optimal solutions. Although the growth in the number of devices leads to a corresponding increase in decision variables, the model continues to solve the problem within reasonable computational times. The allocation results for Scenario 2 as shown in **Table 10**, in which 860 medical devices were assigned to the four technicians. The results show that the numbers of type 4 and type 5 medical devices allocated to Technicians A and B during both regular working hours and overtime hours differed by only one device. This outcome satisfies the workload fairness requirements specified in Eqs. (4)–(5).

Table 9 Labor cost and computational performance of the BILP solution for all three scenarios

Scenario	Base case	1.0	2
Regular labor cost	24,768.75	37,471.88	40,465.6
OT cost	-	710.938	13,576.5
Obj.func.cost	24,768.75	38,182.81	54,042.1
Lower bound	24,758.33	38,154.17	54,025.0
Opt. gap (%)	0.042%	0.075%	0.032%
CPU time	0.2	0.64	0.51

Table 10 The BILP solution of scenario 2

No.	Device type (Reg./OT) Skilled technician (B)																			
	Technician (C)				Technician (D)				Skilled technician (A)						Skilled technician (B)					
	1	OT	2	OT	1	OT	2	OT	3	OT	4	OT	5	OT	3	OT	4	OT	5	OT
1	-	-	-	-	18	-	-	-	2	-	1	-	-	20	-	-	-	1	-	-
2	-	-	-	-	-	12	-	-	2	-	-	-	20	-	-	-	-	2	-	-
3	-	-	-	-	12	-	8	-	-	-	-	-	-	-	-	-	2	-	10	-
4	-	15	-	-	-	3	-	-	-	-	2	-	10	-	4	-	-	-	-	-
5	-	-	-	-	10	-	-	-	-	-	-	-	-	-	-	-	-	-	-	24
6	16	-	8	-	-	-	-	-	-	-	-	-	14	-	-	-	2	-	-	-
7	24	-	2	-	-	-	-	-	-	1	4	-	8	-	-	3	-	-	-	-
8	3	-	-	7	13	-	9	-	-	-	-	-	28	-	-	-	-	4	-	-
9	-	-	4	-	-	-	-	-	-	-	2	-	-	-	-	-	-	-	21	13
10	-	-	-	-	20	-	-	-	-	-	-	6	8	-	-	-	-	-	50	-
11	-	-	18	-	-	-	-	-	-	-	-	-	-	18	4	-	-	-	44	-
12	-	-	-	-	78	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-
13	-	-	-	-	14	-	8	-	4	-	-	-	14	-	-	-	-	-	-	-
14	34	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	4	-	-	-
15	14	-	8	-	-	-	-	-	-	2	-	-	14	-	-	-	-	-	-	-
16	16	-	1	-	-	-	7	-	-	-	-	-	-	-	-	-	-	-	-	-
17	16	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-
18	-	-	-	-	14	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-
19	32	-	-	-	-	-	1	7	-	-	-	-	-	-	-	-	-	-	-	-
20	24	-	-	-	-	-	8	-	-	-	-	-	8	-	-	-	-	-	-	-
Total	179	15	41	7	179	15	41	7	8	3	9	6	12	38	8	3	8	7	12	37
	242				242				188						188					

5.2 Mathematical Model for Daily Operational Planning (ILP)

5.2.1 Illustrative Case Study

To assist the department head in generating a daily operational plan (**Table 11**), an Integer Linear Programming (ILP) model was developed as a decision-support tool. This tool aims to enhance the efficiency and ease of planning for technical personnel, who often manage multiple auxiliary duties—such as electrical repairs, plumbing, and emergency services—beyond their primary maintenance tasks. The optimization is executed on a per-technician basis for each model run, utilizing the

optimized output from the BILP personnel allocation model (**Table 5**) as its primary input. The base-case scenario consisted of 430 medical devices distributed across 20 clinical departments, requiring preventive maintenance by four technicians within a 30-day planning horizon. The ILP model was solved using OpenSolver on a laptop computer equipped with an Intel Core i5-2.11 GHz processor, 16 GB RAM, and Windows 10 Pro. As shown in **Table 12**, the model was solved efficiently for all cases, yielding either optimal or near-optimal solutions, with CPU times of no more than 10.52 seconds and optimality gaps not exceeding 0.30%.

Table 11 Example of a daily medical device maintenance plan required by the department head

Technician	Week	Department	1		
		Device type	1	2	3
A	1	Monday			
		Regular	-	-	-
		Overtime	-	-	-
		Tuesday			
		Regular	-	-	-
		Overtime	-	-	-

Table 12 Comparison of computational performance before and after applying the optimal ILP solution in the base-case scenario

The base case scenario		Before	After
ILP (A)	Time (CPU sec.)	1.02	10.52
	Risk cost	2,219.10	2,037.00
	Lower bound	2,202.49	2,030.86
	Optimality gap	0.75%	0.30%
ILP (B)	Time (CPU sec.)	0.25	0.16
	Risk cost	2,047.80	2,010.80
	Lower bound	2,045.68	2,010.80
	Optimality gap	0.10%	0.11%
ILP (C)	Time (CPU sec.)	0.38	0.09
	Risk cost	2,907.90	2,569.70
	Lower bound	2,907.90	2,569.70
	Optimality gap	0.00%	0.00%
ILP (D)	Time (CPU sec.)	0.28	0.06
	Risk cost	2,443.50	2,547.00
	Lower bound	2,443.50	2,547.00
	Optimality gap	0.00%	0.00%

Table 13 Comparison of cost efficiency before and after applying the optimal ILP solution in the base-case scenario

Model	Objective function cost		Regular-time Labor cost		Overtime Labor cost		Total Labor cost		Labor cost efficiency (%)
	Before	After	Before	After	Before	After	Before	After	
BILP	28,351.6	24,768.8	17,634.4	24,768.8	10,717.2	0.0	28,351.6	24,768.8	12.64%
ILP(A)	2,219.1	2,037.0	5,500.0	7,489.6	2,992.2	0.0	8,492.2	7,489.6	11.8%
ILP(B)	2,047.8	2,010.8	5,234.4	7,437.5	3,375.0	0.0	8,609.4	7,437.5	13.6%
ILP(C)	2,907.9	2,569.7	3,733.3	4,941.7	2,350.0	0.0	6,083.3	4,941.7	18.8%
ILP(D)	2,443.5	2,547.0	3,166.7	4,900.0	2,000.0	0.0	5,166.7	4,900.0	5.2%

5.2.2 ILP Model Validation

As discussed in Section 4.1.2, the current maintenance planning practice under the existing operating conditions relies on manual scheduling and workforce allocation by departmental personnel. The solutions obtained using OpenSolver under the current planning practice and those generated by the optimal ILP-based planning approach for Technicians A, B, C, and D are presented in the before and after columns, respectively, in **Table 14**. The ILP model was solved

efficiently, requiring less than one CPU minute to obtain a solution. The resulting optimality gap was 0.30%, which is below the commonly accepted threshold of 1% for near-optimal solutions. The results indicate that, compared with the current maintenance planning practice, the optimal ILP-based planning approach reduced the total operational risk cost and total labor cost by 4.7% and 12.6%, respectively. In particular, overtime costs were completely eliminated, decreasing to zero under the optimal maintenance plan.

Table 14 Comparison of computational performance and cost before and after applying the optimal ILP solution in the base-case scenario

Base case scenario		Before	After
ILP(A)	Time (CPU sec.)	1.02	10.52
	Optimality gap	0.75%	0.30%
ILP(B)	Time (CPU sec.)	0.25	0.16
	Optimality gap	0.10%	0.11%
ILP(C)	Time (CPU sec.)	0.38	0.09
	Optimality gap	0.00%	0.00%
ILP(D)	Time (CPU sec.)	0.28	0.06
	Optimality gap	0.00%	0.00%
Total	Operational risk cost	9,618.3	9,164.5
	Labor cost		
	Regular-time	17,634.4	24,768.7
	Overtime	10,717.2	0.0
Total labor cost		28,351.6	24,768.7

5.2.3 Performance Evaluation of the ILP Model

As discussed in Section 4.1.3, scenario settings of the three scenarios for the preventive maintenance planning problem are presented in **Table 8**. The solutions obtained for all three scenarios, as presented in **Table 15**, required less than 11 seconds of CPU time, while the optimality gap remained below 0.35% in every case. These results indicate that the solutions can be considered near-optimal solutions. For the first two scenarios, several instances reached optimal solutions with an optimality gap of 0%. In contrast, no optimal solution was obtained in Scenario 2, where the number of medical devices was doubled relative to the base case scenario. This is because the optimality gap remained above 0%, indicating that the solver could not prove global optimality.

Table 15 Operational risk cost and computational performance of the optimal ILP solution for all three scenarios

Scenario	ILP	Time (Sec.)	Risk cost	Lower bound	Gap (%)
Base case	A	10.52	2,037.00	2,030.86	0.30
	B	0.16	2,010.80	2,008.67	0.11
	C	0.09	2,569.70	2,569.70	0.00
	D	0.06	2,547.00	2,547.00	0.00
1.0	A	0.84	3,207.80	3,196.76	0.34
	B	0.34	3,227.10	3,217.70	0.29
	C	0.11	4,031.50	4,030.56	0.02
	D	0.09	4,031.50	4,031.50	0.00
2	A	0.3	4,106.80	4,101.32	0.13
	B	1.08	4,111.90	4,101.80	0.25
	C	0.24	5,355.30	5,353.87	0.03
	D	0.13	5,355.80	5,354.14	0.03

5.3 Sensitivity Analysis on Workforce Capacity Constraints

A sensitivity analysis was performed to evaluate the impact of changes in the right-hand side (RHS) values of the workforce capacity constraints on the performance of the proposed BILP and ILP models. Specifically, the available regular working hours of technicians were reduced while maintaining a 45-day planning horizon and constant overtime availability. Four cases were considered, representing different levels of workforce capacity as shown in **Table 16**.

As described in Section 4.1.3, Case 1.0 corresponds to the base case, in which skilled technicians A and B, as well as general technicians C and D, were each available for up to 4 regular working hours and 3 overtime hours per day. The number of medical devices requiring maintenance was 659, resulting in a total of 5,272 decision variables. In cases 1.1 and 1.2, the regular working hours of skilled technicians A and B were gradually reduced from 4 to 3.5 and 3 hours per day, respectively. In case 1.3, the regular working hours of general technicians C and D were further reduced to 2.5 hours per day, while skilled technicians A and B remained available for 3

regular working hours per day. The resulting total workforce capacity decreased from 75,600 minutes in Case 1.0 to 62,100 minutes in Case 1.3.

5.3.1 The Proposed BILP Model

We performed a sensitivity analysis on the workforce capacity constraints by reducing technician availability from Scenario 1.0 to 1.3. The objective value, workload allocation, overtime utilization, computational time, and optimality gap were compared across the four cases to assess the robustness of the proposed BILP model as shown in **Table 16**.

Table 16 Variations in the Right-Hand Side values of technician working-hour constraints (hrs.)

Scenario	1.0		1.1		1.2		1.3	
	Reg	O	Reg	O	Reg	O	Reg	O
A	4	3	3.5	3	3	3	3	3
B	4	3	3.5	3	3	3	3	3
C	4	3	4	3	4	3	2.5	3
D	4	3	4	3	4	3	2.5	3
Cap	75,600		72,900		70,200		62,100	

The results indicate that as regular-time capacity was reduced, regular labor costs decreased from 37,471.90 to 28,039.58 baht, as shown in **Table 17**, forcing the model to rely more heavily on overtime. Consequently, overtime costs increased substantially from 710.94 to 14,859.38 baht to satisfy preventive maintenance demands. As a result, the overall objective function value increased by approximately 12.4%, rising from 38,182.80 to 42,898.96 baht. Despite these tighter capacity constraints, the proposed BILP model consistently generated near-optimal solutions, maintaining optimality gaps between 0.05% and 0.10%, which are well below the commonly accepted threshold of 1%. Furthermore, solution times remained below one second across all scenarios, demonstrating the model's computational efficiency and stability under varying resource availability.

Table 17 Labor cost and computational performance of the BILP solution for sensitivity analysis

Scenario	1.0	1.1	1.2	1.3
Regular labor cost	37,471.9	34,675.0	31,831.3	28,039.6
OT labor cost	710.94	4,906.2	9,171.88	14,859.3
Obj.func. cost	38,182.8	39,581.2	41,003.13	42,898.9
Lower bound	38,154.17	39,560.42	40,966.67	42,856.25
Gap (%)	0.08	0.05	0.09	0.10
CPU time (Seconds)	0.64	0.69	0.58	0.59

From **Table 17**, the results indicate that as regular-time workforce capacity was systematically reduced, regular labor costs decreased from 37,471.90 to 28,039.58 baht. To satisfy preventive maintenance requirements within the planning horizon, the model increasingly relied on overtime work, resulting in a substantial increase in overtime labor costs from 710.94 to 14,859.38 baht. Consequently, the objective function value increased by approximately 12.35%, rising from 38,182.80 to 42,898.96 baht. Despite the increasingly restrictive workforce capacity constraints, the proposed BILP model consistently generated near-optimal solutions, with optimality gaps ranging from 0.05% to 0.10%, all of which were well below the commonly accepted threshold of 1% for near-optimal solutions. Furthermore, the computational time remained below one second across all scenarios, demonstrating the model's computational efficiency and robustness under varying levels of workforce availability.

5.3.2 The Proposed ILP Model

For the sensitivity analysis on workforce capacity constraints, the results in **Table 18** demonstrate how

changes in available labor capacity affect labor costs and computational performance across the four ILP formulations. The operational risk costs (Objective function costs) of Technicians A, B, C, and D were 14,497.9, 14,538.6, 14,433.8, and 14,403.8 baht, respectively. The values are closely clustered, ranging from 14,403.8 to 14,538.6 baht, with a maximum difference of only 134.8 baht (0.94% of the average value). Since operational risk cost increases with preventive maintenance delay, these results indicate that the proposed model effectively distributes maintenance tasks associated with equipment failure risk among technicians. As shown in **Table 18**, the proposed ILP model was solved efficiently for all cases, yielding either optimal or near-optimal solutions, with optimality gaps not exceeding 0.34%. Moreover, the consistently low computational times (below two seconds) observed across all scenarios demonstrate the robustness and computational efficiency of the proposed model under different workforce availability conditions.

Table 18 Labor cost and computational performance of the ILP solution for sensitivity analysis

Case	Model	Regular-time cost	Overtime cost	Objective function cost	Gap (%)	CPU time (Seconds)
1.0	ILP(A)	11,208.3	312.50	3,207.80	0.34%	0.84
	ILP(B)	11,234.4	398.44	3,227.10	0.29%	0.34
	ILP(C)	7,512.50	-	4,031.50	0.02%	0.11
	ILP(D)	7,516.67	-	4,031.50	0.00%	0.09
1.1	ILP(A)	9,822.92	2,515.63	3,247.50	0.12%	1.06
	ILP(B)	9,822.92	2,390.63	3,228.10	0.21%	0.33
	ILP(C)	7,512.50	-	4,031.50	0.02%	0.13
	ILP(D)	7,516.67	-	4,031.50	0.00%	0.08
1.2	ILP(A)	8,395.83	4,570.31	3,173.10	0.01%	0.18
	ILP(B)	8,406.25	4,601.56	3,197.70	0.11%	0.25
	ILP(C)	7,512.00	-	4,031.50	0.02%	0.11
	ILP(D)	7,516.67	-	4,031.50	0.00%	0.07
1.3	ILP(A)	8,395.83	4,570.31	3,173.10	0.01%	0.18
	ILP(B)	8,406.25	4,601.56	3,197.70	0.11%	0.23
	ILP(C)	5,616.67	2,843.75	4,016.50	0.02%	0.14
	ILP(D)	5,620.83	2,843.75	4,016.50	0.02%	0.13

5.4 Outputs of the BILP and ILP Models Implemented in Ms. Excel

The structures of the BILP and ILP models for the base-case scenario implemented in Excel are presented in **Figures 1 and 2**, respectively. As shown in **Figure 1**, the optimized workforce allocation generated by the BILP model is displayed in cells Q3:AJ22 for technicians A and B. The resulting workforce allocation serves as an input parameter for the subsequent ILP model for technician A. The workload balancing and equitable distribution

constraints are incorporated in cells G4:I11 and Q26:AJ28, respectively. **Figure 2** illustrates the ILP model for technician A, where the workforce allocation obtained from the BILP model is entered in cells D110:M129, and the optimized operational maintenance plan is presented in cells D99:M103. The OpenSolver 2.9.4 solution log files generated for the base-case scenario are shown in **Figures 3 and 4**. **Figure 3** presents the solution log of the BILP model, while **Figure 4** presents the solution log of the ILP model for Technician A.

	A	B	C	D	E	F	G	H	I	C	P	Q	R	S	T	U	V	W	X	Y	Z	AA	AB	AC	AD	AE	AF	AG	AH	AI	AJ						
1	Total Maintenance Time										Dep.	A	A/OT	A	A/OT	A	A/OT	A	A/OT	A	A/OT	AA	AB	AC	AD	AE	AF	AG	AH	AI	AJ						
2											1	1	2	2	3	3	4	4	5	5	1	1	2	2	3	3	4	4	5	5							
3	Technician	Capacity (mn.)	Time Spent (mn.)	Remaining Time (mn.)	Balance dist.										1	0	0	0	0	1	0	1	0	10	0	0	0	0	0	0	0	0	0	0			
4	A	7200	7190	10	A-B	50	<=	80											2	0	0	0	0	1	0	10	0	0	0	0	0	0	1	0	0	0	
5	A/OT	2700	0	2700	B-A	-50	<=	80											3	0	0	0	0	0	0	0	0	0	0	0	0	0	1	0	5	0	
6	B	7200	7140	60	A/OT-B/OT	0	<=	80											4	0	0	0	0	0	1	0	5	0	0	0	0	2	0	0	0	0	
7	B/OT	2700	0	2700	B/OT-A/OT	0	<=	80											5	0	0	0	0	0	0	0	12	0	0	0	0	0	0	0	0	0	
8	C	7200	5930	1270	C-D	50	<=	50											6	0	0	0	0	0	0	0	7	0	0	0	0	0	1	0	0	0	
9	C/OT	2700	0	2700	D-C	-50	<=	50											7	0	0	0	0	1	0	2	0	4	0	0	0	0	1	0	0	0	0
10	D	7200	5880	1320	C/OT-D/OT	0	<=	50											8	0	0	0	0	0	0	0	14	0	0	0	0	0	2	0	0	0	
11	D/OT	2700	0	2700	D/OT-C/OT	0	<=	50											9	0	0	0	0	0	1	0	0	0	0	0	0	0	0	0	17	0	0
12	Total	39600	26140	13460											10	0	0	0	0	0	3	0	1	0	1	0	0	0	0	0	0	0	28	0	0		
13	Maintenance Time Each Dept. (Mn.)										11	0	0	0	0	0	0	0	0	0	0	0	0	0	2	0	0	0	0	0	31	0	0	0			
14	Dept. Name	Demand	Time Spent	Total Cost											12	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0				
15	1	1350	1350	1312.50											13	0	0	0	2	0	0	7	0	0	0	0	0	0	0	0	0	0	0				
16	2	1200	1200	1187.50											14	0	0	0	0	0	0	0	0	0	0	0	0	0	0	2	0	0	0				
17	3	935	935	873.96											15	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0				
18	4	995	995	942.71											16	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0				
19	5	1210	1210	1208.33											17	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0				
20	6	1195	1195	1123.96											18	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0				
21	7	1165	1165	1079.17											19	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0			
22	8	1990	1990	1914.58											20	0	0	0	0	0	0	0	0	4	0	0	0	0	0	0	0	0	0	0			
23	9	1505	1505	1548.96											sum	0	0	0	0	6	0	8	0	81	0	1	0	0	5	0	7	0	81	0			
24	10	2985	2985	3015.63											A-B										B-A												
25	11	2975	2975	3014.58											<=										<=												
26	12	1950	1950	1625.00											-1										0												
27	13	1180	1180	1118.75											<=										<=												
28	14	960	960	822.92											1										1												
29	15	1135	1135	1071.88											<=										<=												
30	16	580	580	483.33											1										1												
31	17	400	400	333.33											<=										<=												
32	18	350	350	291.67											1										1												
33	19	980	980	816.67											<=										<=												
34	20	1100	1100	983.33											1										1												
35	Total	26140	26140	24768.75	<<< Objective Function										<=										<=												

Figure 1 Structure of the BILP model in the base-case scenario implemented in Excel

	A	B	C	D	E	F	G	H	I	J	K	L	M
1	No.			1	2	3	4	5	6				
2	Day			Mon	Tue	Wed	Thur	Fri	Sat				
3	Dept.	type	time	A	A/OT	A	A/OT	A	A/OT	A	A/OT	A	A/OT
99	20	1	50	0	0	0	0	0	0	0	0	0	0
100	20	2	45	0	0	0	0	0	0	0	0	0	0
101	20	3	45	0	0	0	0	0	0	0	0	0	0
102	20	4	55	0	0	0	0	0	0	0	0	0	0
103	20	5	80	0	0	0	0	1	0	0	0	0	0
104	Working/Day (Cap/Day (min.			200	0	220	0	240	0	240	0	225	0
105				240	90	240	90	240	90	240	90	240	90
106	Input												
107				A	A/OT	A	A/OT	A	A/OT	A	A/OT	A	A/OT
108	Dept.			1	1	2	2	3	3	4	4	5	5
109				0	0	0	0	1	0	1	0	10	0
110				0	0	0	0	1	0	0	0	10	0
111				0	0	0	0	0	0	0	0	0	0
112				0	0	0	0	0	0	1	0	5	0
113				0	0	0	0	0	0	0	0	12	0
114				0	0	0	0	0	0	0	0	7	0
115				0	0	0	0	1	0	2	0	4	0
116				0	0	0	0	0	0	0	0	14	0
117				0	0	0	0	0	0	1	0	0	0
118				0	0	0	0	0	0	3	0	1	0
119				0	0	0	0	0	0	0	0	0	0
120				0	0	0	0	0	0	0	0	0	0
121				0	0	0	0	0	0	0	0	0	0
122				0	0	0	0	2	0	0	0	7	0
123				0	0	0	0	0	0	0	0	0	0
124				0	0	0	0	1	0	0	0	7	0
125				0	0	0	0	0	0	0	0	0	0
126				0	0	0	0	0	0	0	0	0	0
127				0	0	0	0	0	0	0	0	0	0
128				0	0	0	0	0	0	0	0	0	0
129				0	0	0	0	0	0	0	0	4	0
130													
131													

Figure 2 Structure of the ILP model for Technician A in the base-case scenario implemented in Excel

6. Conclusions

This study proposed a spreadsheet-based optimization framework for workforce allocation and operational planning in medical device preventive maintenance management. The framework consists of two Integer Linear Programming models: a BILP model for workforce allocation, and an ILP model for operational planning. The proposed BILP model incorporates technician skill requirements, workload balance, and equitable distribution constraints to ensure a fair and efficient allocation of preventive maintenance tasks among technicians. This study employs a sequential

optimization framework. Workforce allocation decisions are determined first, while detailed maintenance scheduling is subsequently performed at the operational level using the allocation results as input. This sequential structure simplifies the optimization process, reduces computational complexity, improves solution efficiency, and makes the model more practical for implementation in a spreadsheet environment. The computational results demonstrated that the proposed models effectively generated feasible and high-quality maintenance plans while minimizing labor costs. Compared with the current maintenance planning practice, the BILP and ILP models reduced labor costs by 12.64% and 12.60%, respectively.

In addition, the BILP model achieved balanced workloads among technicians within the same skill group and ensured equitable task distribution, with differences in assigned devices not exceeding one device per technician. Sensitivity analysis further confirmed the robustness of the proposed approach under varying resource capacities, producing near-optimal solutions with optimality gaps below 1% and solution times of less than one minute. The results demonstrate the scalability of the proposed model, as it maintains acceptable solution quality and computational performance even as the number of medical devices increases. The proposed spreadsheet-based implementation provides a practical and low-cost decision-support tool that can be readily adopted by healthcare organizations without requiring specialized optimization software. Future research may extend the models to incorporate corrective maintenance activities, uncertainty in maintenance durations and technician availability, and multi-period planning environments to further enhance maintenance management effectiveness.

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	A	B	C	D	E
1	Welcome to the CBC MILP Solver				
2	Version: 2.9.4				
3	Build Date: Oct 4 2015				
4					
24	Result - Optimal solution found (within gap tolerance)				
25					
26	Objective value:	24768.75000000			
27	Lower bound:	24758.333			
28	Gap:	0.00			
29	Enumerated nodes:	0			
30	Total iterations:	0			
31	Time (CPU seconds):	0.20			

Figure 3 The solution log of the BILP model

	A	B	C	D	E
1	Welcome to the CBC MILP Solver				
2	Version: 2.9.4				
3	Build Date: Oct 4 2015				
45					
46	Result - Optimal solution found (within gap tolerance)				
47					
48	Objective value:	2037.00000001			
49	Lower bound:	2030.858			
50	Gap:	0.00			
51	Enumerated nodes:	183			
52	Total iterations:	1113			
53	Time (CPU seconds):	10.52			

Figure 4 The solution log of the ILP model for Technician A

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