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Development of a Mathematical Model for Multi-Location Training Center Timetabling Problem: A Case Study at the Yogyakarta Industrial Training Center

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ABSTRACT

The background of the research is based on the complexity of manual scheduling, which leads to workload imbalances, schedule conflicts, and decreased participant satisfaction. This study aims to develop a mathematical model to optimize the scheduling of multi-location training at the *Yogyakarta Industrial Training Center*. The Integer Programming method is applied to formulate scheduling problems by considering key variables such as the availability of human resources, type of training, location, and duration. Secondary data in the form of training recapitulation for 2021–2024 were used for model validation. The results show that this model is effective in reducing workload imbalance (100% within the normal category) and minimizing schedule violations to below 10 violations per year in the optimal HR formation (10-10-10-8). Sensitivity analysis revealed that the addition of human resources in the finance division (Division 4) was a critical factor in handling the increase in training volume. Simulations involving 500 trainings proved the resilience of the model, with a computing time of 4 hours. The study's conclusions highlight the potential of implementing the model to improve operational efficiency and participant satisfaction. Practical implications include dynamic HR allocation recommendations and the development of automated scheduling systems based on this model. This research contributes to the literature on scheduling optimization with a measurable approach for government training institutions.

Keywords: Training center; timetabling problem; mathematical model; Integer Programming; workload distribution; scheduling efficiency.

INTRODUCTION

The scheduling of activities in training institutions plays a crucial role in ensuring the effectiveness and efficiency of training program implementation. Optimal scheduling not only impacts the smooth operation of the institution but also affects the quality of training outcomes and participant satisfaction. The main goal of scheduling is to optimize one or more objectives, such as resource utilization, conflict minimization, and equitable workload distribution (Choi et al., 2017; Kristiadi & Hartanto, 2019; Urva & Sellyana, 2019; Wicaksono & Putra, 2021; Yunita et al., 2018). Without proper scheduling, training institutions may face various issues, including workload imbalances, time conflicts, and inefficiencies in the use of human resources.

The process of scheduling work teams at training institutions is complex. It involves a variety of dynamic variables and constraints, including the type of training, location, duration, and availability of human resources in various roles such as teachers, coordinators, and support staff. This complexity is heightened by the need to avoid overlapping schedules and ensure fair and balanced workloads among team members. Additionally, external factors such as sudden changes in training or policy requests from agencies or government bodies often increase the challenge. If not properly managed, these factors can negatively impact the performance and quality of the training (Nugraha, 2020).

Conventional scheduling methods, such as manual or spreadsheet-based approaches, are often inadequate for handling the scale and complexity of scheduling in large, dynamic training institutions (Khairunisak & Hendriyani, 2021; Mauluddin et al., 2018; Pambudi et al., 2021). These methods typically result in inefficient schedules, lengthy preparation times, schedule conflicts among personnel, and uneven workload distribution. Such inefficiencies can compromise the quality of training and the overall performance of the team (Nugroho, 2020). Therefore, a more sophisticated and adaptive approach is necessary to address these challenges effectively.

Integer Programming modeling offers a powerful mathematical framework for optimally formulating scheduling problems with measurable constraints. Solutions for these models can be found using exact methods, metaheuristic algorithms (such as genetic algorithms, simulated annealing, tabu search), or hybrid approaches depending on the model's complexity. Exact methods are suitable for exploring all possible solutions in small to medium-sized problems (Wirawan, 2017), while metaheuristic methods help search for near-optimal solutions in large-scale cases (Santoso & Ai, 2017). Hybrid methods combine multiple metaheuristic techniques to provide more efficient solutions for complex scheduling problems (Priambodo et al., 2016). These advanced approaches bring advantages in model flexibility, computational efficiency, and the ability to overcome limitations present in manual scheduling.

The Yogyakarta Industrial Education and Training Center (BDI Yogyakarta) is a technical implementation unit under the Head of the Industrial Education and Training Center (Pusdiklat Industri) of the Ministry of Industry. It uses a 3-in-1 system that integrates training, competency certification, and job placement within a single workflow. As one of Indonesia's industrial training institutions, BDI Yogyakarta faces increasing challenges in managing its growing training programs. According to the 2024 Monitoring and Evaluation Report of the Yogyakarta Industrial Training Center, the number of training batches expanded sharply from 89 batches across 6 training types in 2020 to 214 batches with 10 types in 2021—an increase of 104%, driven by the implementation of online training during the COVID-19 pandemic. Subsequent years saw fluctuations, with 116 batches in 2022 across 6 types, 120 batches in 2023 across 11 types, and a forecast of 104 batches with 9 training types in 2024 (Yogyakarta Industrial Education and Training Center, 2024).

With rising training demand, time constraints, and limited human resources, optimal scheduling has become an urgent necessity. The preparation of monthly work team schedules currently requires a lengthy process (approximately 5 working days), leading to a short timeframe for personnel to prepare before trainings commence. This situation may adversely affect the quality of training and participant satisfaction. The 2024 Monitoring and Evaluation Report highlights a decline in participant satisfaction with committee performance over the past two years, declining by 0.32% in 2023 and 1.8% in 2024. If this trend continues unchecked, it could negatively impact the institution's reputation, stakeholder trust, and participant engagement.

Full Time Equivalent (FTE) is a workload analysis method that measures the time needed to complete tasks and converts it into an FTE index. The FTE can also be calculated by comparing total employee workloads with target workloads. This method is commonly used to measure efficiency and determine human resource needs. FTE values are categorized as overload, normal, or underload (Tridoyo and Sriyanto, 2014). According to workload analysis guidelines from the State Civil Service Agency (2010), an FTE index above 1.28 indicates overload; between 1.00 and 1.28 is normal; and between 0 and 0.99 indicates underload or insufficient workload.

Previous relevant studies include Mokhtari et al. (2021), who developed a mathematical model for university lecture scheduling targeting minimizing lecturer schedule violations, reducing student travel time, and optimizing classroom capacity through exact methods. Despite successfully reducing conflicts, they faced high computational times for large-scale problems. Rosyidi et al. (2019) created an exam scheduling model using Integer Programming focused on balancing lecturer workloads and minimizing schedule collision penalties, though the model was less flexible for dynamic resource changes.

This research contributes to developing more efficient and effective scheduling models for training institutions. By leveraging Integer Programming and optimal solution search methods, it aims to provide better approaches to equitable workload distribution and conflict minimization. The outcomes are intended not only for implementation at the Yogyakarta Industrial Training Center but also for adaptation by other industrial training institutions facing similar challenges. Moreover, this research can serve as a foundation for future development of more sophisticated, responsive automated scheduling systems.

Currently, the scheduling process at the Yogyakarta Industrial Training Center is manual, relying on standard spreadsheets without dedicated solvers or automatic scheduling applications. This results in complicated, complex schedules that often neglect even workload distribution. Consequently, inefficiencies arise from either overburdened or underutilized personnel, which harms training quality, customer satisfaction (including industry partners and participants), and overall team performance. Developing mathematical models using Integer Programming and searching for optimal scheduling solutions is expected to address these issues effectively.

The study aims to develop an optimal mathematical model for work team scheduling that accounts for factors such as human resource availability, number of trainings, locations, and training duration. It also seeks to analyze the model's effectiveness in resolving workload imbalances and finding efficient optimal solutions for complex scheduling problems. Comparing optimized results with conventional scheduling methods currently used will hopefully inform recommendations to improve automated scheduling systems at the Yogyakarta Industrial Training Center and similar institutions.

This research offers theoretical contributions to the scheduling optimization literature and practical benefits for training institutions and decision-makers. The expected outcomes include direct application at the Yogyakarta Industrial Training Center and adoption by other institutions to optimize work team schedules, thereby improving operational efficiency, ensuring fair workload allocation, and maintaining or enhancing training quality and participant satisfaction. For decision-makers, the study provides useful models and insights to optimize human resource use, reducing time and costs in managing complex scheduling tasks.

METHOD

This study focused on the Yogyakarta Industrial Training Center, which operates under the Ministry of Industry of the Republic of Indonesia and organizes training based on a 3-in-1 system. Activities at the Training Center were divided into five main areas: training development and cooperation, training implementation, competency certification, job placement, and monitoring and evaluation. The research concentrated on the training implementation process, which encountered complex scheduling problems involving variables such as training type, location, duration, and human resource availability across divisions. Consequently, a mathematical model was developed to account for these factors and constraints to produce an optimal schedule.

Secondary data were used, including training recaps, work team schedules, and competency-based program documents. Tools employed in the study included Microsoft Excel for data management, Microsoft Word for reporting, and Python with Gurobi for modeling and optimization.

The research process began with a literature review, followed by data collection and mathematical model development. The model was then verified and validated to ensure accuracy and alignment with real-world conditions. Optimal solutions were sought primarily using exact methods, with metaheuristic approaches applied if necessary. The optimized results were compared to existing schedules to assess improvements in workload distribution. Sensitivity analysis was performed to evaluate the impact of parameter changes on outcomes. Finally, conclusions and recommendations were formulated to enhance the efficiency and effectiveness of scheduling at the Yogyakarta Industrial Training Center and similar institutions.

RESULT AND DISCUSSION

Sensitivity Analysis

The function of sensitivity analysis is to understand how changes in the input parameters of a model affect the output of that model. The first sensitivity analysis in this study was conducted to see how changes in the number of human resources in each division affect the results of the work team's scheduling. A second sensitivity analysis was conducted to see how strong the model maintains workload balance as the number of trainings increases. The initial epsilon value is set at 10. This value is assumed from the maximum violation tolerance limit of 1 violation per month, taking into account the number of effective months in a year is 10 months. If no feasible solution is found at this epsilon limit, then the epsilon value will be gradually increased until a solution that meets the limit is obtained. This approach aims to maintain a balance between a fair distribution of workload and minimizing constraint violations, especially when the number of human resources is limited.

Total HR Scenario

By trying various scenarios for the number of human resources, we can find out if the schedule made is still running well, as well as see if there is a violation of the set rules. The results of this analysis help in determining the ideal number of human resources so that the workload remains balanced and schedule conflicts do not occur. The sensitivity analysis related to the number of human resources was tested through three scenarios, namely:

1. The number of human resources in each division varies ± 2 people,
2. The number of human resources is evenly distributed in all divisions,
3. The number of human resources is evenly distributed except in the finance division.

The results of sensitivity analysis with various scenarios of the number of human resources are shown in Tables 1, 2 and 3.

Table 1. Sensitivity Analysis of the Number of Human Resources Scenario 1

Year	Number of Training	Number of Locations	Number of human resources					Workload (FTE)			Number of Violations			
			Divided 1	Divided 2	Divided 3	Divided 4	Total	Underload	Normal	Overload	Location Constraints	Constraint Bentrok	Constraint Max_Training	Total
2021	214	27	6	10	8	4	28	0%	100%	0%	0	25	25	50
			7	11	9	5	32	0%	100%	0%	0	3	17	20
			8	**12**	**10**	**6**	**36**	**0%**	**100%**	**0%**	**0**	**0**	**10**	**10**

			9	13	11	7	40	0%	100%	0%	0	0	7	7
			10	14	12	8	44	0%	100%	0%	0	0	3	3
2022	116	26	8	9	8	4	29	0%	100%	0%	0	3	7	10
			9	10	9	5	33	0%	100%	0%	0	3	5	8
			10	**11**	**10**	**6**	**37**	**0%**	**100%**	**0%**	**0**	**2**	**2**	**4**
			11	12	11	7	41	0%	100%	0%	0	1	2	3
			12	13	12	8	45	0%	100%	0%	0	0	0	0
2023	120	29	5	10	10	4	29	0%	100%	0%	0	8	2	10
			6	11	11	5	33	0%	100%	0%	0	4	0	4
			7	**12**	**12**	**6**	**37**	**0%**	**100%**	**0%**	**0**	**0**	**0**	**0**
			8	13	13	7	41	0%	100%	0%	0	0	0	0
			9	14	14	8	45	0%	100%	0%	0	0	0	0
2024	104	32	5	7	13	6	31	0%	100%	0%	0	13	12	25
			6	8	14	7	35	0%	100%	0%	0	0	15	15
			7	**9**	**15**	**8**	**39**	**0%**	**100%**	**0%**	**0**	**1**	**9**	**10**
			8	10	16	9	43	0%	100%	0%	0	0	10	10
			9	11	17	10	47	0%	100%	0%	0	0	10	10

Source: Data is processed from the results of the Integer Programming model simulation based on secondary data from the Yogyakarta Industrial Training Center (2023)

Table 2. Sensitivity Analysis of the Number of Human Resources Scenario 2

Year	**Number of Training**	**Number of Locations**	**Number of human resources**					**Workload (FTE)**			**Number of Violations**			
			Divided 1	**Divided 2**	**Divided 3**	**Divided 4**	**Total**	**Underload**	**Normal**	**Overload**	**Location Constraints**	**Constraint Bentrok**	**Constraint Max_Training**	**Total**
2021	214	27	7	7	7	7	28	0%	100%	0%	0	2	23	25
			8	8	8	8	32	0%	100%	0%	0	0	15	15
			9	9	9	9	36	0%	100%	0%	1	1	8	10
			10	10	10	10	40	0%	100%	0%	0	4	3	7
			11	11	11	11	44	0%	100%	0%	1	2	0	3
2022	116	26	7	7	7	7	28	0%	100%	0%	0	1	4	5
			8	8	8	8	32	0%	100%	0%	0	0	0	0
			9	9	9	9	36	0%	100%	0%	0	0	0	0
			10	10	10	10	40	0%	100%	0%	0	0	0	0
			11	11	11	11	44	0%	100%	0%	0	0	0	0
2023	120	29	7	7	7	7	28	0%	100%	0%	0	5	0	5
			8	8	8	8	32	0%	100%	0%	0	0	0	0
			9	9	9	9	36	0%	100%	0%	0	0	0	0
			10	10	10	10	40	0%	100%	0%	0	0	0	0
			11	11	11	11	44	0%	100%	0%	0	0	0	0
2024	104	32	8	8	8	8	32	0%	100%	0%	0	0	20	20
			9	9	9	9	36	8,33%	86,11%	5,56%	0	0	10	10
			10	10	10	10	40	0%	95,00%	5,00%	0	0	10	10

			11	11	11	11	44	0%	93,18%	6,82%	0	0	5	5
			12	12	12	12	48	0%	100%	0%	0	1	4	5

Source: Data is processed from the results of the Integer Programming model simulation based on secondary data from the Yogyakarta Industrial Training Center (2023)

Table 3. Sensitivity Analysis of the Number of Human Resources Scenario 3

Year	Number of Training	Number of Locations	Number of human resources					Workload (FTE)			Number of Violations			
			Divided 1	Divided 2	Divided 3	Divided 4	Total	Underload	Normal	Overload	Location Constraints	Constraint Bentrok	Constraint Max_Training	Total
2021	214	27	7	7	7	6	27	0%	100%	0%	0	1	29	30
			8	8	8	6	30	0%	100%	0%	0	1	14	15
			9	9	9	6	33	0%	100%	0%	0	1	11	12
			10	10	10	6	36	0%	100%	0%	0	1	9	10
			11	11	11	6	39	0%	100%	0%	0	0	7	7
2022	116	26	7	7	7	6	27	0%	100%	0%	0	1	4	5
			8	8	8	6	30	0%	100%	0%	0	2	1	3
			9	9	9	6	33	0%	100%	0%	0	2	0	2
			10	10	10	6	36	0%	100%	0%	0	0	1	1
			11	11	11	6	39	0%	100%	0%	0	0	1	1
2023	120	29	7	7	7	6	27	0%	100%	0%	1	2	2	5
			8	8	8	6	30	0%	100%	0%	0	0	0	0
			9	9	9	6	33	0%	100%	0%	0	0	0	0
			10	10	10	6	36	0%	100%	0%	0	0	0	0
			11	11	11	6	39	0%	100%	0%	0	0	0	0
2024	104	32	7	7	7	8	29	0%	100%	0%	0	7	21	30
			8	8	8	8	32	0%	100%	0%	0	0	20	20
			9	9	9	8	35	11,43%	82,86%	5,71%	0	0	10	10
			10	10	10	8	38	0%	94,74%	5,26%	0	0	10	10
			11	11	11	8	41	0%	100%	0%	0	0	10	10
			12	12	12	8	44	0%	100%	0%	0	0	7	7

Source: Data is processed from the results of the Integer Programming model simulation based on secondary data from the Yogyakarta Industrial Training Center (2023)

Based on the sensitivity analysis conducted, it is known that the variation in the number of human resources in each division has a direct impact on the number of violations and the efficiency of the work team's scheduling. This analysis is carried out by trying various scenarios for the number of human resources, namely by adding and decreasing personnel in each division in a certain range.

Scenario 1: Number of human resources in each division ±2

The first scenario explores the change in the number of human resources in each division in the range of ±2 people. This aims to see how fluctuations in the number of human resources affect the distribution of workload and violations that occur. The main results of this scenario:

1. Regardless of the variation in the number of HR, all configurations indicate that the workload is in the 100% normal category. This means that the model is able to divide tasks evenly among available personnel, without underloading or overloading. This reflects the effectiveness of the model in managing workloads, even as the number of human resources changes.
2. Violations of constraints such as clashing training schedules and the maximum number of training per month for each personnel decrease as the number of human resources increases, suggesting that adding human resources provides greater scheduling flexibility and improves the ability to handle training spread across different times and locations.
3. The number of human resources that is too small (e.g. only 5-7 people per division) leads to a significant increase in violations. This is due to the limited combination of work teams that can be formed, so that schedule and workload conflicts cannot be avoided.

Scenario 2: The number of human resources is evenly distributed across all divisions

Scenario 2 is designed to observe the impact of equalizing the number of human resources across divisions, with equal numbers between Divisions 1, 2, 3, and 4. The goal is to evaluate whether an even HR allocation strategy between divisions is able to provide scheduling efficiency, workload balance, and minimize violations of constraints. The main results of this scenario:

1. In general, the workload in this scenario is in the 100% normal category on most configurations, especially when the total human resources are in the range of 36 to 44 people. In smaller HR formations (e.g. 8 people per division), there are a numberof deviations kit, such as the emergence of underload (8.33%) and overload (5.56%). However, when the number of human resources is even and large enough (≥10 per division), the distribution of workload is stable again, reaching 100% normal.
2. With an even allocation of human resources, the scheduling system has better flexibility to form work teams without having to rely excessively on specific divisions. This has an impact on reducing constraint violations, especially schedule clash violations and violations of the maximum training per month for each personnel.
3. The pattern that looks quite consistent: the higher the number of human resources per division (with an even distribution), the lower the number of violations. This shows that the existence of a backup of HR in each division increases the likelihood of team formation without schedule conflicts or overload.
4. Just like the previous scenario, the epsilon constraint method is applied with an epsilon initial value = 10, based on the assumption of a maximum of 1 violation per month in the 10 effective months per year. Most configurations in this scenario can meetthe Epsilon bat without the need to increase their value, especially in formations with ≥9 human resources per division. This means that the strategy of equalizing the number of human resources between divisions is quite effective in producing feasible solutions without many violations.

Scenario 2 shows that an even HR allocation strategy between divisions has a positive impact on the stability of workload distribution and significantly reduces constraint violations. What's more, the scheduling system is able to accommodate training tasks efficiently without causing location conflicts or over-assignments. This strategy has also been proven to be in accordance with the epsilon constraint approach, because many feasible solutions are found without the need to raise the epsilon value from the initial limit.

Scenario 3: The number of human resources is evenly distributed, except for the finance division

Scenario 3 is designed to reflect real conditions, where the number of human resources in Division 4 (finance division) is relatively fixed each year. This is due to the specification of expertise in the financial sector that is not easily replaced by personnel from other divisions. Therefore, this sensitivity analysis evaluates the impact of increasing the number of human resources only in Divisions 1, 2, and 3, while the number of human resources in Division 4 is maintained at 6 or 8 people. The main outcomes of this scenario are:

1. Almost all configurations indicate that workloads are in the normal category, even with a limited number of human resources. Although certain formations such as 8-9-9-6 and 9-9-9-6 have workload deviations (underload 11.43% and overload up to 5.71%), most of them remain within good tolerance limits.
2. One of the key findings of this scenario is that the number of violations cannot be fully suppressed by simply adding human resources in Divisions 1–3. This can be seen from:
   a) The 9-9-9-6 formation still produces 30 violations, with the dominance on the maximum number of training constraints.
   b) In contrast, when Division 4 was also increased to 8 men (e.g. 10-10-10-8 formation), the offense decreased to 10, showing that Division 4's capacity also greatly determined the success of the scheduling.
3. The most violations come from the maximum limit on the number of training per individual. This happens because the limitation of human resources in Division 4 causes personnel in the division to be assigned more often, exceeding the maximum allowed limit. This did not happen much in the previous scenario that increased the number of human resources in a balanced manner in all divisions.
4. As in the previous scenario, the epsilon constraint approach is used with a starting limit of $\varepsilon = 10$. In this scenario, only configurations with Division 4 numbering ≥ 8 people meet the epsilon limit. Configurations with a 6-man 4 Division often exceed that limit, so it is necessary to raise epsilon to get a feasible solution. This confirms that the limitation of human resources in one critical division can be a dominant factor in the increase in system violations.

Scenario 3 shows that an increase in the number of human resources in three divisions alone (1, 2, and 3) is not enough to eliminate violations if Division 4 remains restricted. This is due to the limitations of the 4th Division's personnel making them too often scheduled, exceeding the maximum allowable task. Therefore, a more appropriate strategy would be to consider minimal upgrades in Division 4, especially when the amount of training and locations is large enough. The application of the epsilon constraint method in this scenario makes it clear that a feasible and optimal solution can only be obtained if all divisions, including divisions with special specializations, have adequate human resource allocation.

The Impact of Training Data Distribution

In addition to the number and distribution of human resources, the results of this sensitivity analysis are also greatly influenced by the pattern of distribution of training data itself. A tight amount of training in a given time or concentration of training in a specific location will add pressure to the scheduling system. For example, if there are many training sessions in one month that are of long duration and involve the same location, then the likelihood of schedule conflicts or location clashes will increase, especially if human resources are limited. Therefore, the availability of adequate human resources must be supported by the arrangement of training schedules that are evenly distributed in time and location.

From the overall sensitivity analysis related to the number of human resources, it can be concluded that:

1. The number of human resources greatly affects scheduling flexibility. The greater the number of human resources, the less likely it is to occur.
2. A balanced distribution between divisions is essential. Even though the total number of human resources is sufficient, the imbalance in the number of personnel between divisions can still cause problems.
3. Divisions with specific HR specifications such as finance require special attention, as limited personnel can be a critical point in the scheduling system even if other divisions are optimal.
4. The distribution of training data affects the system load. Scheduling will be more optimal if the training is evenly distributed in terms of time, location, and type of training.
5. The scheduling model is quite robust, because in most variations in the number of HR, scheduling results remain optimal with normal workloads and minimal breaches.

These results can be used as a reference in planning human resource needs for each period, as well as as a basis for strategic decision-making to maintain optimal operational performance.

Scenario Number of Training

This sensitivity analysis was conducted to evaluate the effect of variations in the number of training on HR allocation, workload distribution, and constraint violations, which include location violations, schedule clashes, and exceeding the maximum limit of training per individual. Based on the results of the sensitivity analysis to the number of human resources, especially in Scenario 3, it was found that the optimal human resource formation is one that is able to produce no more than 10 violations per year. This limit is determined based on the assumption of a maximum tolerance of 1 violation per month, with a total of 10 effective months of training implementation in one year. The formations that meet these criteria are 10-10-10-6 and 10-10-10-8, which means that they each consist of 10 people in Divisions 1, 2, and 3, as well as 6 or 8 people in Division 4. In addition to successfully keeping violations below the threshold, these two formations also show a workload distribution of more than 90% in the normal category, indicating that the division of tasks between personnel takes place fairly and proportionately. Based on this, the sensitivity analysis to the number of training is then focused on the following two scenarios:

1. Scenario 1: 10-10-10-6 HR formation, with variations in the number of training between 100 to 500 batches.
2. Scenario 2: 10-10-10-8 HR formation, with variations in the number of training between 100 to 500 batches.

These two scenarios aim to test the extent of the resilience of HR formations to the surge in the number of trainings, as well as to see the dynamics of changes in workload and the number of constraint violations as the volume of training activities increases. The results of the sensitivity analysis with the number of training scenarios can be seen in Tables 4 and 5.

Table 4. Sensitivity Analysis of Number of Training Scenarios 1

Number of Training	Number of human resources					Workload (FTE)			Number of Violations				Compute Time (Hours)
	Division 1	Division 2	Division 3	Divided 4	Total	Underload	Normal	Overload	Location Constraints	Constraint Bentrok	Constraint Max_Training	Total	
100	10	10	10	6	36	0%	100%	0%	0	0	0	0	< 1
150	10	10	10	6	36	0%	100%	0%	0	0	0	0	
200	10	10	10	6	36	0%	100%	0%	0	0	0	0	
250	10	10	10	6	36	0%	100%	0%	0	0	0	0	
300	10	10	10	6	36	0%	100%	0%	0	2	3	5	
350	10	10	10	6	36	0%	100%	0%	0	2	8	10	3
400	10	10	10	6	36	0%	100%	0%	0	2	13	15	3.5
450	10	10	10	6	36	0%	100%	0%	0	7	18	25	4
500	10	10	10	6	36	0%	100%	0%	0	5	25	30	6

Source: Data is processed from the results of the Integer Programming model simulation based on secondary data from the Yogyakarta Industrial Training Center (2023)

Table 5. Sensitivity Analysis of Number of Training Scenarios 2

Number of Training	Number of human resources					Workload (FTE)			Number of Violations				Compute Time (Hours)
	Divided 1	Divided 2	Divided 3	Divided 4	Total	Underload	Normal	Overload	Location Constraints	Constraint Bentrok	Constraint Max_Training	Total	
100	10	10	10	8	38	0%	100%	0%	0	0	0	0	< 1
150	10	10	10	8	38	0%	100%	0%	0	0	0	0	
200	10	10	10	8	38	0%	100%	0%	0	0	0	0	
250	10	10	10	8	38	0%	100%	0%	0	0	0	0	
300	10	10	10	8	38	0%	100%	0%	0	0	0	0	
350	10	10	10	8	38	0%	100%	0%	0	0	0	0	
400	10	10	10	8	38	0%	100%	0%	0	0	5	5	3
450	10	10	10	8	38	0%	100%	0%	0	0	10	10	4
500	10	10	10	8	38	0%	100%	0%	0	0	20	20	4

Source: Data is processed from the results of the Integer Programming model simulation based on secondary data from the Yogyakarta Industrial Training Center (2023)

Scenario 1: 10-10-10-6 formation with variations in the number of training between 100 to 500 batches.

This scenario uses an HR formation with 10 people in each of Divisions 1, 2, and 3, and 6 people in Division 4. This configuration was previously considered quite efficient and feasible for the number of training of up to 250 batches based on the results of HR sensitivity analysis. In this scenario, a variation of the number of training is carried out ranging from 100 to 500 batches to test the capacity limit of the formation in maintaining workload balance and minimizing constraint violations. The main outcomes of this scenario are:

1. Although the number of training has increased to 500 batches, the distribution of workloads remains in the normal category of 100%, demonstrating the resilience of the model in distributing tasks fairly despite relatively limited human resources.

2. When the number of training reaches 300 batches, violations of constraints appear, especially at the maximum limit of training per individual, namely the number of training 300: 5 violations, the number of training 400: 15 violations and the number of training 500: 30 violations. This showed that a formation with only 6 men in Division 4 was starting to become overwhelmed with handling the growing training load.
3. There was an increase in computing time from less than 1 hour (for 100–300 trainings) to 6 hours on 500 trainings, indicating increased processing complexity.

Scenario 2: 10-10-10-8 formation with a variation in the number of training between 100 to 500 batches.

This scenario is a development of the previous scenario, where the number of human resources in Division 4 (finance) was increased to 8 people. This addition is based on real conditions in 2024, where there is an additional allocation of 2 people in the Finance Division. The goal is to overcome the limited capacity of the division, which in the previous scenario was the main source of violations due to overcrowded assignments. Similar to Scenario 1, the number of training is varied from 100 to 500 batches to evaluate the extent to which these formations are able to maintain the stability of the scheduling system and minimize constraint violations. The main outcomes of this scenario are:

1. The addition of human resources in Division 4 (from 6 to 8 people) has a significant impact on maintaining a balanced work distribution even up to 500 trainings.
2. Although the number of trainings increased, the number of violations remained much lower than in Scenario 1, which was 400 trainings: only 5 violations and 500 training numbers: only 10 violations. This proves that adding human resources in the division that was previously a "bottleneck" is very effective in reducing violations.
3. The processing time is relatively lower than scenario 1, with a maximum time of 4 hours for 500 trainings. This shows that feasible solutions can be found faster with more adequate HR formation.

Overall, in the sensitivity analysis of the number of trainings, it was concluded that:

1. Scenario 1 shows limitations in handling large amounts of training, mainly due to the limitations of human resources in Division 4. Violations increased significantly at 400–500 trainings, exceeding the established epsilon limit (10).
2. Scenario 2 is much more stable and optimal, with a ≤ 20 violation for the number of training reaches 500. This reinforces the previous conclusion that the increase in HR in Division 4 significantly improves the flexibility of the system and the quality of the management solution.
3. The 10-10-10-8 formation is more recommended for long-term and large training scenarios because it has better performance in terms of the number of breaches, workload distribution, and compute efficiency.

CONCLUSIONS

This study successfully developed and validated a mathematical model for scheduling work teams at the Yogyakarta Industrial Training Center by considering critical factors such as human resource availability, training number, location, and duration. The model accurately reflected real conditions and demonstrated significant improvements over conventional methods by reducing workload imbalances, minimizing schedule conflicts, enhancing resource utilization, and streamlining scheduling time with better documentation. These results support more efficient and precise decision-making in complex scheduling scenarios. For practical implementation, a gradual adoption of the model is recommended, accompanied by operator training and integration with existing information systems, while future system development should focus on flexibility, user-friendly interfaces, cost considerations, and personnel preferences to ensure sustainability. Further research is suggested to explore hybrid optimization methods, test the model's adaptability across other institutions, conduct deeper sensitivity analyses, and involve stakeholders in joint validation to ensure the model's practical applicability beyond theoretical contexts.

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