



RESOURCE ALLOCATION OPTIMIZATION USING MIXED INTEGER PROGRAMMING WITHIN MISSION ESSENTIAL TASKS OF MILITARY TRAINING IN THE NIGERIAN DEFENCE ACADEMY

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Abstract

The Nigerian Defence Academy (NDA) is responsible for training officer cadets to ensure their proficiency in mission essential tasks. However, managing resources while maintaining proficiency can be challenging and costly. This study aimed to minimize the cost of training while maintaining proficiency by improving resource allocation through optimization techniques. The study developed a Mixed Integer Programming (MIP) model implemented through the TORA software, to determine the optimum distribution of resources and training among each task at a minimum cost. The results showed that the proposed optimization technique significantly improved the allocation of resources to various training tasks, with an achieved objective function value of 211.5 representing the minimum cost required to maintain proficiency. The study's findings provide a sound scientific and qualitative basis for optimal decision-making, considering the sensitivity of defence in any nation. The study's contribution to the optimization of military training in the NDA can significantly improve resource allocation for various training tasks, which is crucial in any nation's defence.

Keywords: Resource allocation, Optimization, Mission essential tasks, Mixed integer Programming, military training

INTRODUCTION

The Nigerian Defence Academy (NDA) is a military training institution that conducts Mission Essential Tasks (METs) requiring efficient resource allocation for optimal results (Nigerian Defence Academy, n.d). Military training is a vital activity of the NDA, and it is necessary to optimize the resources allocated to these activities for optimal results. Resource allocation optimization involves identifying the resources required to achieve a set of objectives and

allocating them to maximize the objectives' attainment (Liu et al., 2022). METs in military training include combat operations, logistics, intelligence gathering, and communication, which require the allocation of resources such as personnel, equipment, and time to ensure effective training (U.S. Air Force, n.d).

The optimization process involves balancing the trade-offs between different resources and maximizing the objectives of the training. Mathematical models and data analytics are two



approaches used for resource allocation optimization in complex systems such as the NDA (Liu et al., 2022). Mathematical models are useful for identifying the METs, the resources required for these tasks, and the optimal allocation of resources to maximize the objectives of the training. On the other hand, data analytics can be used to analyze historical data on resource allocation and identify areas for improvement (Yang & Xia, 2021).

Resource allocation optimization within METs of military training in the Nigerian Defence Academy (NDA) is an essential research topic that aims to ensure efficient allocation of resources to achieve optimal results. Research in this area will provide insights into the optimal allocation of resources in the NDA, which will contribute to the effective training of officers for critical mission.

Therefore, the efficient allocation of resources is crucial to the NDA's success in achieving its objectives. The use of mathematical models and data analytics can be beneficial in optimizing resource allocation within METs of military training in the Nigerian Defence Academy. Continued research in this area will provide valuable insights for decision-makers, which can lead to improved efficiency and effectiveness in military training.

LITERATURE REVIEW

Zhou et al (2021) proposed a unified knowledge graph-based decision-making framework that integrates the implicit engineering knowledge in machining workshop environment. The framework was used for supporting the optimal method of resource allocation and mine implicit relationships between complex engineering data to enrich the relationship between workshop resources and efficiently guide production. They presented a three-staged method of candidate device formation and community-based device evaluation in the mixed-model production process, which uses the workshop resource knowledge graph (WRKG) to provide relatedness data support for the formation and evaluation of candidate devices. The results indicated that the method can generate a more logical and intuitive resource reconfiguration process knowledge to improve the device utilization rate, the response capability of processing tasks and the flexibility of devices under the premise of stable processing.

The availability of assets crucially depends on the interplay between the facility locations, workforce planning, and capacity allocation. Therefore, Turan et

al. (2021) modeled and solved a novel multi-objective optimization problem for strategic facility location, workforce planning, and capacity allocation in the context of the military. The developed model adapts a dynamic capacity scheme for both the workforce and facilities to capture the dynamic nature of future demand, such as maintenance requirements for assets. However, the simulation model neither suggests nor seeks the best solution strategy or strategies. To overcome this shortcoming, they proposed a simulation–optimization approach that uses a Non-dominated Sorting Genetic Algorithm-II (NSGA-II) to generate feasible solution strategies (candidate solutions) such as time and amount of capacity expansion and downsizing for both the workforce and facilities as well as the amount of crew recruitment. These solution strategies were fed to the simulation model where it evaluates the fitness of candidate solutions.

At present, the problem of optimal allocation of resources has been applied in many fields, among which support personnel optimization is the main force and core (Wang, 2011).

Song et al. (2021) proposed a model for vehicle maintenance support using a non-linear integer programming and improved fruit fly optimization algorithm for personnel allocation optimization. Firstly, a workload model was constructed for vehicle equipment by analyzing scheduled maintenance, natural random failure, and combat damage. In view of the situation where there are enough human resources, the prediction model of the number of personnel with the minimum total number as the goal is constructed to achieve the purpose of saving human resources. Mixed integer nonlinear programming problem (MINP) toolbox was used to solve the prediction model of the number of personnel, in view of the shortage of maintenance personnel, a maintenance personnel allocation model aiming at minimizing maintenance time is constructed to maximize maintenance efficiency. In order to solve the model, the fruit fly optimization algorithm (FOA) was improved for global optimization ability of the algorithm. Finally, simulations were applied to verify the effectiveness of the optimization method of the model and provide a certain theoretical basis for maintenance personnel to optimize decision-making.

The optimization of training of personnel is an important research content of support force allocation. The reasonable allocation of maintenance personnel and the adjustment of the number of



technical personnel at various levels can enable the effectiveness of a military organization to have a reasonable structure of technical personnel as tasks can be completed in a timely and efficient manner, and resource allocation can obtain maximum benefits (Song et al., 2021).

Research on the optimal allocation of personnel within MET is of great significance for improving efficiency of the organization and exerting resource efficiency.

However, the existing personnel optimization research focuses on the enterprise or industrial background and does not consider the MET. The established model is mainly aimed at nonmaintainable professional technical personnel, which is not suitable for the optimization of training personnel of military (Santos et al., 2021). Kim and Yoon (2015); Shi et al. (2019) analyzed the maintenance support process and construct a maintenance personnel allocation model and a demand forecast model based on queuing theory. Zhang et al. (2019) also analyzed the influencing and restrictive factors of military ship equipment, establishes a maintenance personnel optimization model with the smallest cumulative repair time, and solves the model by using a hybrid genetic algorithm. Su et al. (2018) proposed an optimization model for maintenance personnel equipment to minimize labor costs and designs an enhanced mixed integer linear programming algorithm to solve the model. An accurate analysis of military personnel training within MET frameworks serves as a prerequisite for effectively reducing training costs and facilitating the implementation of optimal resource allocation support programs.

In light of this, the present study focuses on the military training of Army Cadets at the NDA over their final 12-month period, during which cadets strive to achieve proficiency in essential tasks crucial to their successful performance. These tasks are classified into METs and minor categories. The METs encompass military tactics, weapon training, map reading, signal communication, internal security, physical training, equitation, and drill exercise. On the other hand, the minor tasks include current affairs, computer application, driving and maintenance, organization and administration, field engineering, military writing, man management, military law, French, and first aid. Within the context of this study, the major tasks are considered as METs, thereby constituting the central focus. Each MET is

incorporated into a mixed integer programming model. The objectives of this model are to optimize performance levels at predetermined time points, maximize specific physiological and performance adaptations through structured training interventions, mitigate the risk of overtraining, and foster long-term development.

DATA COLLECTION AND ANALYSIS

At the final year level of the training program, a deliberate decision was made to select eight METs that would encompass a comprehensive range of critical military training activities. This choice was made due to the unique nature of the cadets' training progression at the NDA. Throughout the course of their training, the first four years were dedicated to a combination of academic activities and military training. However, in the final year, the focus shifted entirely towards intensive military training.

To ensure that the final year cadets were equipped with the necessary skills and knowledge essential for military operations, a meticulous process was undertaken to select the appropriate METs. These METs were deliberately chosen to cover a diverse range of fundamental military competencies. Each MET was assigned a distinct code name ranging from t1 to t8. This nomenclature facilitated ease of reference and coordination throughout the training program.

The selection of these METs for the final year cadets served a twofold purpose. Firstly, it allowed for the consolidation of the cadets' previous academic and military training experiences into a culminating year solely dedicated to honing their military skills. This concentrated focus provided the cadets with an optimal environment to refine their capabilities and apply their knowledge to practical military scenarios.

Secondly, the chosen METs were specifically designed to encompass a broad spectrum of essential skills required for effective military operations. By carefully curating this set of tasks, the training program aimed to equip the cadets with a well-rounded skill set that would be invaluable in their future military careers. The METs covered various aspects, including military tactics, weapon training, map reading, signal communication, internal security, physical training, equitation, and drill exercise. These METs were carefully chosen to cover essential skills and knowledge required for military operations. Each task was assigned a code name from t1 to t8 for easy reference.



In addition to these eight METs, various training modes were identified to provide a comprehensive training experience. These training modes included Communication Exercise (Comm Ex), Advance & Quick Attack Technical Exercise Without Troops (A & Q ATTK TEWT), Sand Modeling Exercise (SM Ex), Harbour TEWT (Harb TEWT), Defence TEWT (DEF TEWT), Deliberate Attack (DEL ATTK), Withdrawal TEWT (WDR TEWT), Patrol & Ambush (PATR & AMB), Map Reading (MR), Slow & Quick Match (S&Q M), Skill at Arms & Bayonet fight (SAA BAF), and Obstacles Crossing (OBST CRS). Each training mode was assigned a code name from m1 to m12 for easy reference and coordination.

To model the given tasks effectively, a mixed integer programming (MIP) problem was formulated using the set of METs and training modes as input data. The MIP problem allowed for optimization and analysis of the tasks, ensuring efficient allocation of resources and personnel for training purposes.

In the model problem, equation (1) represents the formulation used to address the training requirements. Within this formulation, several parameters and variables are defined to represent specific aspects of the training scenario.

Firstly, the parameter "n" is introduced, where n = 106 represent the total number of cadets in the final year class who are to be trained on each of the METs. This parameter indicates the scale of the training program, as it involves a considerable number of cadets.

Furthermore, the parameter "p" is specified as 36, 35, and 35, representing the number of cadets in each platoon considered for the training program. The three platoons encompass the entire cohort of cadets participating in every session of each training mode for the study. This distribution allows for efficient organization and coordination of training activities across the platoons.

Therefore, these combined elements provide the necessary context and parameters to model the training program effectively. The formulation takes into account the number of cadets, platoon distribution, proficiency levels, and constraints on the number of MET assignments, enabling the development of an optimized solution for the given training tasks.

The Army training mix model by KG Murty (1994) was applied for the minimization of the training cost. The model is described with the following equations:

$$\text{Minimize total cost (Z)} = \sum_{m=1}^r \left(\frac{n}{p} C_m Y_m \right) \dots\dots\dots (1)$$

$$\text{Subject to: } \sum_{tm=1}^r a_{tm} x_{tm} \geq b_t \dots\dots\dots (2)$$

and

$$0 \leq x_{tm} \leq u_{tm} \dots\dots\dots (3)$$

Note that equations (4) and (5) were used to calculate the parameters of b_t and a_{tm} :

$$b_t = \text{standard level} - \text{ZPM for METs} \dots\dots\dots (4)$$

$$a_{tm} = (PR_{tm}(U_{tm}) - PR_{tm}(0)) / U_{tm} \dots\dots\dots (5)$$

The notations for all the data in the model above are:

Z = Total cost of training

n = Total number of cadets who need training.

p = number of persons who participate simultaneously in each session of the training.

C_m = Cost (sum of the operational costs) per session of training mode m.

Y_m = the number of repetitions of mode m towards satisfying the proficiency constraint.

r = the number of times mode m is repeated during the cycle.

tm = task and mode (event and technique) of training of the tasks.

a_{tm} = average slope of the learning curve for the task-mode pair (t, m) in the range of interest $0 \leq r \leq U_{tm}$.

U_{tm} = upper bound on the number of repetitions of mode m that count towards satisfying the proficiency retention constraint corresponding to t.

b_t = the minimal proficiency retention needed at the end of the training cycle in order to satisfy the proficiency constraint corresponding to t.

PR_{tm} = proficiency retention for the task-mode pair (t, m)

To ensure a standardized proficiency level for each MET, the standard proficiency level is set at 0.60. This value indicates the expected level of competence that cadets are required to achieve in the specific tasks outlined by the METs. The proficiency level serves as a benchmark for evaluating the effectiveness and success of the training program.

Additionally, the variable "r" is introduced, representing the maximum number of METs that a



cadet can be assigned to. In this context, r is limited to a value less than or equal to 10, indicating that each cadet can be assigned to a maximum of ten METs. This constraint ensures that cadets have a focused and manageable workload, allowing them to effectively develop their skills and knowledge within a specific set of METs.

The Zero Practice Minimum (ZPM) and the upper bound on the number of repetitions of mode m that count towards satisfying the proficiency retention constraint corresponding to $t(U_{tm})$ for all the platoons is shown in Table 2.0.

TABLE 1.0: Lists of tasks, training mode and their code names

List of Tasks	Code Name	Training Mode	Code Name	Task-mode (tm) for each task.
Military tactics	t_1	Comm Ex	m_1	$t1m1, t1m2, t1m3, t1m4, t1m5, t1m6, t1m7, t1m8, t1m12$
Weapon training	t_2	A & Q Attk	m_2	$t2m1, t2m4, t2m11$
Map reading	t_3	SM Ex	m_3	$t3m1, t3m3, t3m9$
Signal communication	t_4	Harb TEWT	m_4	$t4m1, t4m2, t4m4, t4m8$
Internal security	t_5	Def TEWT	m_5	$t5m1, t5m5, t5m6, t5m7, t5m8$
Physical training	t_6	Del Attk	m_6	$t6m1, t6m12$
Equitation	t_7	Wdr TEWT	m_7	$t7m1, t7m10$
Drill exercise	t_8	Patr & Amb	m_8	$t8m1, t8m10$
-	-	MR	m_9	-
-	-	S&Q M	m_{10}	-
-	-	SAA Baf	m_{11}	-
-	-	Obst Crs	m_{12}	-

TABLE 1.0 represents a list of METs and their corresponding training modes. The table provides a mapping between tasks and training modes, where each task is associated with specific training modes.

In mixed integer programming, decision variables are often used to represent choices or assignments related to tasks. In this table, the tasks are represented by code names (t_1, t_2, t_3 , etc.), and each task has a corresponding training mode (Comm Ex, A & Q Attk, SM Ex, etc.) and task mode (m_1, m_2, m_3 , etc.).

The task modes (tm) represent specific variations or subtasks within each task. For example, for the Military tactics task (t_1), there are multiple task modes ($t1m1, t1m2, t1m3$, etc.) associated with it. Similarly, other tasks (t_2, t_3, t_4 , etc.) have their respective task modes depending on the difficulty of the task.

In a mixed integer programming model, decision variables can be defined to represent the assignment or

selection of specific task modes for each task. These decision variables can be binary (0 or 1) to indicate whether a particular task mode is selected or not.

The table provides a structure and reference for formulating the decision variables and constraints in the mixed integer programming model by associating the tasks, training modes, and task modes.

TABLE 2.0 presents the upper bounds for the repetition of training modes in a platoon-based training. Each row represents a specific task (t) that needs to be trained, and the table provides information about the number of modes used (m), the number of days allocated for the training for the cadets to master the tasks, and the upper bounds for the repetition of training modes in the three platoons (Platoon-1, Platoon-2, Platoon-3). It is important to note that a combination of platoons forms a company.



TABLE 2.0: (Upper Bound of Repetition of Training Mode)

Task (t)	No of Mode Used (m)	No of Days	Platoon-1 (U_{tm})	Platoon-2 (U_{tm})	Platoon-3 (U_{tm})
t ₁	9	3	09	09	07
t ₂	3	2	06	05	04
t ₃	3	2	06	05	05
t ₄	4	4	08	10	08
t ₅	5	2	10	07	06
t ₆	2	2	04	06	05
t ₇	2	2	04	06	05
t ₈	2	3	06	06	06

For example:

- Task t₁ requires the use of 9 different training modes. The training is scheduled for 3 days, and in Platoon-1, each mode will be repeated 9 times, in Platoon-2, each mode will be repeated 9 times, and in Platoon-3, each mode will be repeated 7 times.
- Task t₂ involves 3 training modes and is scheduled for 2 days. In Platoon-1, each mode will be repeated 6 times, in Platoon-2, each mode will be repeated 5 times, and in Platoon-3, each mode will be repeated 4 times.

The table provides similar information for the remaining tasks (t₃ to t₈), indicating the number of modes used, the number of training days, and the upper bounds for mode repetition in each platoon.

This table is valuable for planning and organizing METs, ensuring that each task is adequately covered within the given time frame and that the training modes are distributed effectively among the platoons.

The approximated (calculated) average slope of the learning curve (a_{tm}) using the formula in equation (5) for each platoon are given in the Table 3.0, 4.0 and 5.0.

TABLE 3.0: (Average Slope of Learning Curve of Platoon-1)

Task(t)	(U_{tm})	ZPM	$PR_{tm}(U_{tm})$	a_{tm}	b_t
t ₁	09	0.54	0.95	0.05	0.06
t ₂	06	0.36	0.80	0.07	0.24
t ₃	06	0.50	0.80	0.05	0.10
t ₄	08	0.50	0.90	0.05	0.10
t ₅	10	0.13	1.00	0.09	0.47
t ₆	04	0.24	0.70	0.12	0.36
t ₇	04	0.19	0.70	0.13	0.41
t ₈	06	0.28	0.80	0.09	0.32

The values in Tables 3.0, 4.0, and 5.0 represent the average slope of the learning curve (a_{tm}) and the minimum proficiency retention needed at the end of the training cycle (b_t) for each task (t) in Platoon-1, Platoon-2, and Platoon-3, respectively. These values were derived based on the provided information and calculations.

The ZPM values, representing proficiency retention with no practice, were given for each task. The $PR_{tm}(U_{tm})$ values, indicating proficiency retention at the upper bound of repetitions, were also provided. These values were used to determine the a_{tm} values.

The U_{tm} values, specifying the maximum number of repetitions for each training mode, were obtained



from Table 2.0. By substituting the $PR_{tm}(U_{tm})$ and $PR_{tm}(0)$ values into Equation (5), the a_{tm} values were calculated.

TABLE 4.0: (Average Slope of Learning Curve of Platoon-2)

Task(t)	(U_{tm})	ZPM	$PR_{tm}(U_{tm})$	a_{tm}	b_t
t_1	09	0.54	0.95	0.05	0.06
t_2	05	0.36	0.75	0.08	0.24
t_3	05	0.50	0.75	0.05	0.10
t_4	10	0.50	1.00	0.05	0.10
t_5	07	0.13	0.85	0.10	0.47
t_6	06	0.24	0.80	0.09	0.36
t_7	06	0.19	0.80	0.10	0.41
t_8	06	0.28	0.80	0.09	0.32

The values in Tables 3.0, 4.0, and 5.0 represent the average slope of the learning curve (a_{tm}) and the minimum proficiency retention needed at the end of the training cycle (b_t) for each task (t) in Platoon-1, Platoon-2, and Platoon-3, respectively. These values were derived based on the provided information and calculations.

The ZPM values, representing proficiency retention with no practice, were given for each task. The

TABLE 5.0: (Average Slope of Learning Curve of Platoon-3)

Task(t)	(U_{tm})	ZPM	$PR_{tm}(U_{tm})$	a_{tm}	b_t
t_1	07	0.54	0.85	0.04	0.06
t_2	04	0.36	0.70	0.09	0.24
t_3	05	0.50	0.75	0.05	0.10
t_4	08	0.50	0.90	0.05	0.10
t_5	06	0.13	0.80	0.11	0.47
t_6	05	0.24	0.75	0.10	0.36
t_7	05	0.19	0.75	0.11	0.41
t_8	06	0.28	0.80	0.09	0.32

The minimal proficiency retention (b_t) was determined by subtracting the ZPM values from the standard level of 0.60, as indicated by Equation (4).

By following these calculations and utilizing the provided information, the average slope of the learning curve (a_{tm}) and the minimal proficiency retention (b_t) values for each task in Platoon-1, Platoon-2, and Platoon-3 were derived and presented in Tables 3.0, 4.0, and 5.0, respectively.

$PR_{tm}(U_{tm})$ values, indicating proficiency retention at the upper bound of repetitions, were also provided. These values were used to determine the a_{tm} values.

The U_{tm} values, specifying the maximum number of repetitions for each training mode, were obtained from Table 2.0. By substituting the $PR_{tm}(U_{tm})$ and $PR_{tm}(0)$ values into Equation (5), the a_{tm} values were calculated.

RESULT

The Problem Formulation and the Training Model Solution

In the study, the obtained values from Tables 3.0, 4.0, and 5.0, along with equations 1, 2, 3, and 4, were utilized to formulate an Integer Programming Problem. The objective was to minimize the total cost (Z) associated with the training model solution. The Min Z (the objective function) in the Integer



The grid in Figure 1.0 is a representation of the problem's input data and mathematical expressions that include coefficients, constraints, and variables.

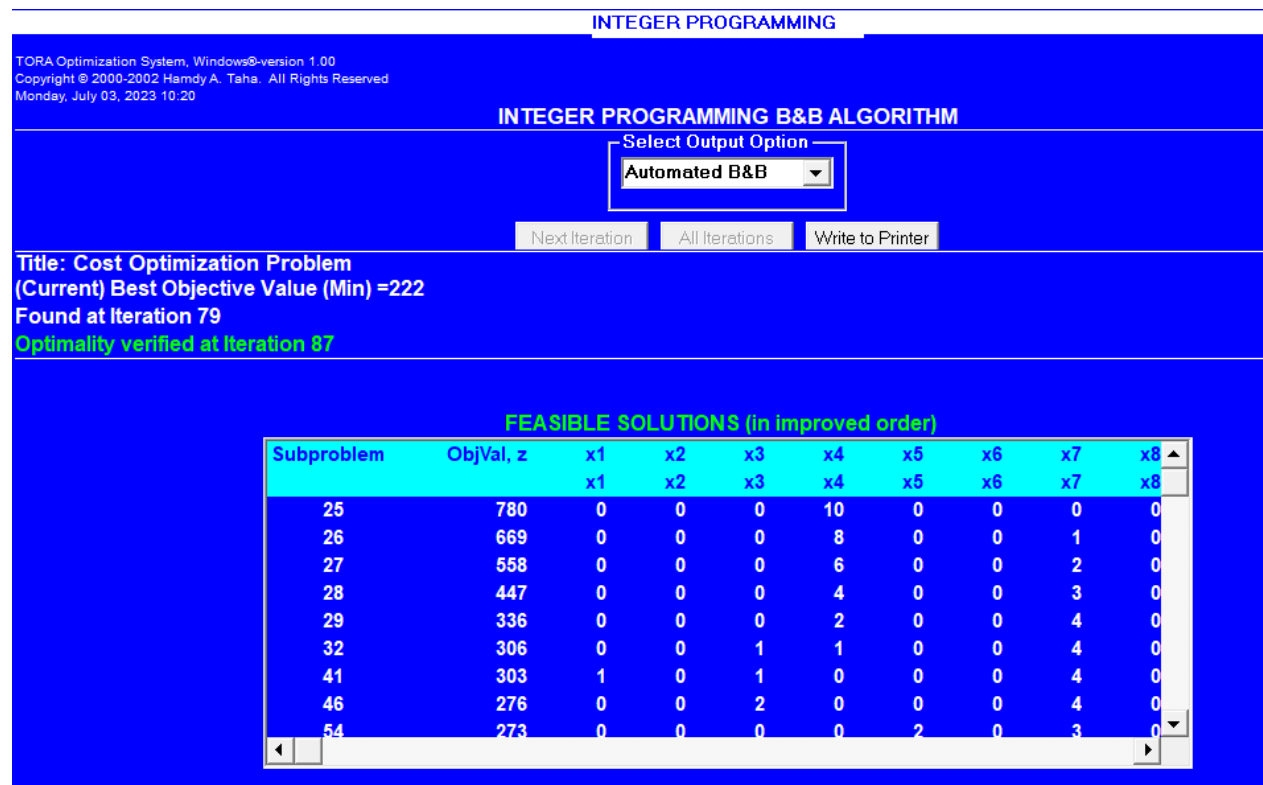


Figure 2.0: Feasible Solutions and Objective Values in Cost Optimization

Figure 2.0 depicts the Integer Programming Branch and Bound (B&B) algorithm, implemented in TORA software, to tackle a cost optimization problem. It provided output that detailed the iterative process of finding feasible solutions, prioritizing them based on their objective values. The objective was to minimize the objective value, indicating the overall cost in this context. The output presented the feasible solutions in an improved order, meaning that each solution met all the problem constraints and was ranked according to its lower objective value. The study aimed to identify the solution with the minimum objective value, representing the most cost-effective outcome within the given constraints.

The output from Figure 3.0 reveals that the user-guided B&B algorithm has achieved a solution with an objective function value of 211.5. Specific values

for most decision variables are provided, indicating progress in the optimization process.

Discussion of Results

By conducting a cost optimization analysis using the TORA software and the Integer Programming Branch and Bound (B&B) algorithm, we obtained a solution with a minimum objective function value of 211.5. This value represents the maximum allowable cost for training in a specific platoon on a particular task, given that the proficiency retention cycle is strictly followed. The study provided valuable insights into the learning curve, objective function values, and decision variable assignments. These findings showcase the effective application of mathematical optimization techniques in addressing cost optimization problems.

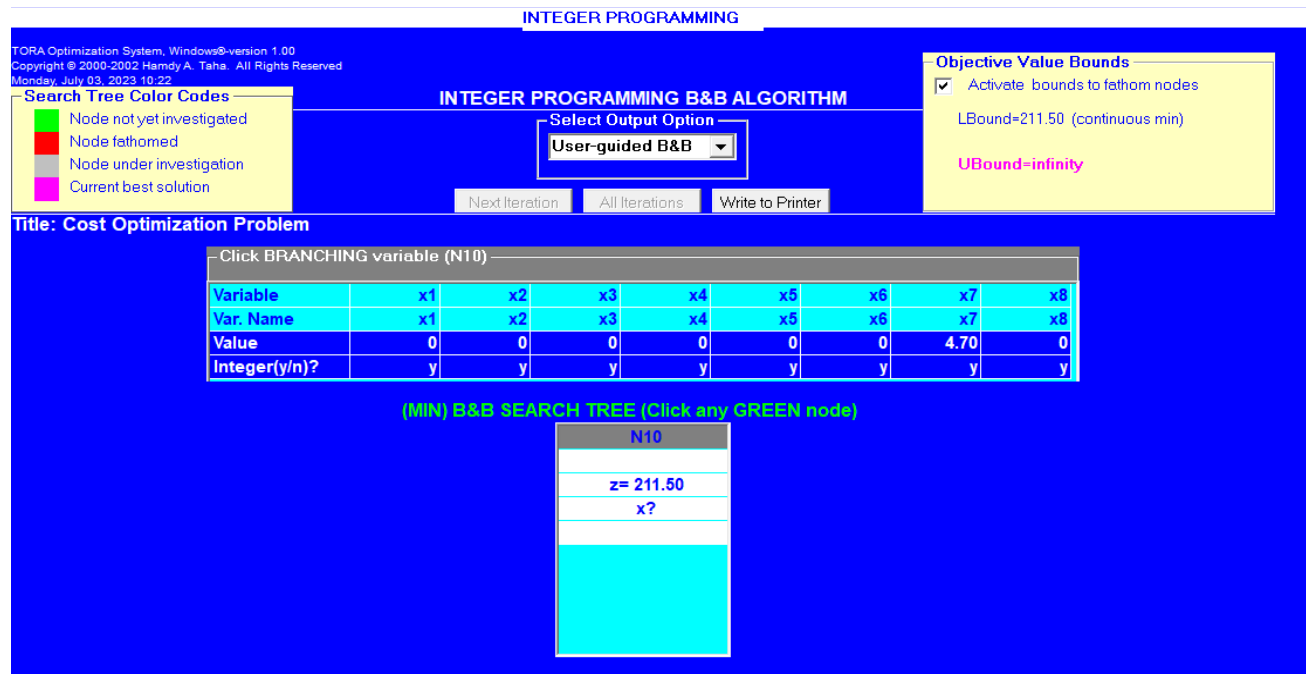


Figure 3.0: Output for Minimum Objective Function

CONCLUSION

This study aimed to minimize the cost of training cadets while ensuring their proficiency, providing the NDA management with a scientific and qualitative foundation for optimal decision-making in defence. Three significant advancements were made in this study to enhance resource management for training officer cadets. Firstly, an effective improvement was achieved through the utilization of optimization techniques for resource allocation. Secondly, the cost and tasks were successfully modeled as an integer programming problem. Lastly, the study achieved optimum optimization of training costs.

The results of this research make a valuable contribution to the optimization of military training, particularly in the allocation of resources within the NDA Army wing for various training tasks. By leveraging mathematical optimization techniques, the study enables more efficient resource allocation and cost reduction. These findings offer a practical and evidence-based approach to decision-making, which is crucial in sensitive defence contexts. Thus, this research provides a significant advancement in resource management for training officer cadets and holds promising implications for enhancing the overall effectiveness and efficiency of military training programs.

REFERENCES

- Kim, S. W., & Yoon, B. K. (2015). A study on the optimal allocation of maintenance personnel in the naval ship maintenance system. *Journal of the Korea Academia-Industrial Cooperation Society*, 16(3), 1853-1862.
- Liu, Y., Zhu, Y., Bin, Y., & Chen, N. (2022). Resources allocation optimization algorithm based on the comprehensive utility in edge computing applications. *Mathematical Biosciences and Engineering: MBE*, 19(9), 9147-9167.
- Nigerian Defence Academy. (n.d.). About NDA. Retrieved from <https://www.nda.edu.ng/>
- Santos, F., Fukasawa, R., & Ricardez-Sandoval, L. (2021). An integrated machine scheduling and personnel allocation problem for large-scale industrial facilities using a rolling horizon framework. *Optimization and Engineering*, 22(4), 2603-2626.
- Shi, L. H., Chen, J., Ye, Z. Q., & Cheng, X. (2019). Requirement analysis of POL equipment maintenance personnel based on queuing theory. *Command Control and Simulation*, 41(1), 136-140.



- Song, W., Lei, Z., Le, Q., Li, F., & Wu, J. (2021). Maintenance Personnel Optimization Model of Vehicle Equipment Based on Support Task. *Mathematical Problems in Engineering*, 2021.
- Su, X., Han, W., Wu, Y., Zhang, Y., & Liu, J. (2018). A proactive robust scheduling method for aircraft carrier flight deck operations with stochastic durations. *Complexity*, 2018
- Turan, H. H., Kahagalage, S. D., Jalalvand, F., & El Sawah, S. (2021). A multi-objective simulation–optimization for a joint problem of strategic facility location, workforce planning, and capacity allocation: A case study in the Royal Australian Navy. *Expert Systems with Applications*, 186, 115751.
- U.S. Air Force. (n.d.). Air Force Joint Technical Training Environment. Retrieved from <https://www.af.mil/About-Us/Fact-Sheets/Display/Article/104501/air-force-joint-technical-training-environment/>
- Wang, Y. (2011). Predication and optimization of maintenance resources for weapon system. *International Journal of Intelligent Systems and Applications*, 3(5), 1.
- Yang, M., & Xia, E. (2021). A systematic literature review on pricing strategies in the sharing economy. *Sustainability*, 13(17), 9762.
- Zhang, H. Q., Lu, Y. C., & Wang, M. (2019). Optimal allocation of crew support in war time ships based on hybrid genetic algorithm. *Journal of Gun Launch and Control*, 44(4), 37-43.
- Zhou, B., Bao, J., Li, J., Lu, Y., Liu, T., & Zhang, Q. (2021). A novel knowledge graph-based optimization approach for resource allocation in discrete manufacturing workshops. *Robotics and Computer-Integrated Manufacturing*, 71, 102160.

