INSTABRIGHT e-GAZETTE
ISSN: 2704-3010
Volume VII, Issue II
November 2025
Available online at https://www.instabrightgazette.com

OPTIMIZING FACULTY WORKLOAD DISTRIBUTION WITH START-END TIME CONSTRAINTS USING A HYBRID RULE-BASED AND MACHINE LEARNING APPROACH

ROSALIE ALEJANDRO
La Consolacion University of the Philippines
rosalie.alejandro@lcup.email.edu.ph

ABSTRACT

This research presents a combined rule-based and machine learning approach to improve faculty workload scheduling. It addresses the limitations of traditional manual methods. The system was developed through a design and development research process. It takes into account institutional rules, past workload data, and faculty preferences. Hard constraints are handled with rule-based logic, while machine learning forecasts the best workload assignments under flexible conditions. Testing revealed a significant reduction in scheduling conflicts, a better balance in teaching hours, and high satisfaction with preferred time slots. The results indicate that this hybrid approach effectively improves fairness and efficiency in faculty workload distribution. Future studies may broaden its application and consider additional scheduling factors.

Keywords: *Automated Scheduling, Constraint Satisfaction, Educational Resource Management, Faculty Workload Distribution, Hybrid Scheduling Approach, Machine Learning, Rule-Based System, Start–End Time Constraints, Timetabling Optimization, Workload Fairness*

INSTABRIGHT e-GAZETTE
ISSN: 2704-3010
Volume VII, Issue II
November 2025
Available online at https://www.instabrightgazette.com

INTRODUCTION

Faculty workload distribution in academic settings is still a challenge. Traditional manual and rule-based scheduling methods often lead to inefficiencies and unfair task allocation. These methods usually do not effectively consider start and end time constraints or faculty preferences, which are important for ensuring fairness and boosting productivity [1], [2]. This paper presents a hybrid system that combines rule-based logic and machine learning to improve faculty workload distribution while following institutional policies and accommodating individual preferences [3], [9].

The system was developed using a design and development research framework. It integrates institutional policies, historical workload records, and faculty survey data [1], [4], [5]. Hard constraints were addressed through rule-based logic, while a supervised machine learning model predicted optimal workload assignments based on soft constraints, enabling more flexible and personalized scheduling [6], [9]. This combination aims to align institutional standards with the actual needs and preferences of faculty members [2], [7].

Evaluation results show that the hybrid approach significantly reduced scheduling conflicts by 82% and improved workload equity—reducing the variance in faculty teaching hours from 6.5 to 2.1 hours. Additionally, it satisfied 91% of start and end time preferences and achieved an 89% prediction accuracy in forecasting workload demands [8], [9]. These findings suggest that such a system can greatly enhance efficiency, reduce scheduling errors, and promote fairness in workload distribution [3], [10].

In conclusion, combining rule-based systems with machine learning provides a scalable and practical solution to the ongoing challenges in faculty workload management. It is recommended that institutions implement similar hybrid approaches while ensuring regular system updates, continuous feedback collection, and periodic retraining of the machine learning component. Future enhancements could also include modeling additional constraints such as research commitments, administrative responsibilities, and preferred teaching patterns [1], [6], [7].

RELATED REVIEW

Faculty workload distribution and scheduling have been widely studied due to their impact on institutional efficiency and faculty satisfaction. Johnson et al. [1] emphasize the need for data-driven approaches to redefine workload metrics, highlighting limitations in conventional models that often overlook individual preferences and dynamic constraints. Ludwig-Beymer et al. [2] further evaluated a new teaching workload model, demonstrating improved balance but also identifying persistent challenges in accommodating flexible scheduling demands.

Several studies have proposed decision support and automated scheduling systems to address these challenges. Perez Ortega et al. [3] developed an online scheduling system integrating faculty loading within a decision support framework, which showed promising results in handling complex constraints. Similarly, Campanilla et al. [8] created a web-based pre-loading system that streamlines faculty workload allocation, reducing manual errors and administrative burdens. However, many existing systems primarily rely on rule-based logic and lack adaptive mechanisms to predict or learn from workload patterns.

To enhance scheduling flexibility and fairness, machine learning and optimization algorithms have recently been explored. Austero et al. [9] applied a heuristically enhanced whale optimization algorithm to optimize workloads and room utilization, achieving significant improvements in efficiency. Okahana et al. [7] experimented with randomized trials to address workload disparities, showing that algorithmic interventions can support equitable distribution. Despite these advances, combining machine learning with rule-based frameworks remains relatively underexplored.

The reviewed literature underscores the importance of hybrid approaches that integrate institutional rules with predictive modeling to better accommodate faculty preferences and institutional policies. This study builds on prior work by proposing a hybrid system that leverages rule-based logic for hard constraints and machine learning for

INSTABRIGHT e-GAZETTE
ISSN: 2704-3010
Volume VII, Issue II
November 2025
Available online at https://www.instabrightgazette.com

optimizing flexible workload assignments, thereby addressing identified gaps and improving workload fairness and efficiency [4], [5], [6], [10].

METHODOLOGY

This study uses the Software Development Life Cycle (SDLC) framework to design, develop, and evaluate a hybrid faculty workload distribution system. This system combines rule-based logic and machine learning techniques. The SDLC process consists of five main phases: requirements analysis, system design, implementation, testing, and maintenance.

In the requirements analysis phase, we collected and examined data on institutional policies, historical workload records, and faculty preferences. This helped us identify hard constraints, such as fixed schedules and mandatory teaching loads, and soft constraints, like preferred start and end times and teaching sequences. Feedback from faculty and administrative staff refined our system requirements.

The system design phase included creating a hybrid framework. We developed rule-based logic to handle hard constraints and institutional policies, ensuring strict compliance. At the same time, we designed a supervised machine learning model to predict optimal workload assignments. This model learned from historical data and considered faculty preferences, addressing the soft constraints.

During the implementation phase, we integrated the rule-based engine and machine learning model into a single system. We trained the machine learning component using labeled historical workload data to forecast balanced assignments that satisfied faculty preferences. We also developed software modules to manage input processing, check constraints, predict assignments, and generate schedules.

The testing phase used simulations to create faculty workload schedules under different scenarios. We evaluated system performance using metrics like scheduling conflict

INSTABRIGHT e-GAZETTE
ISSN: 2704-3010
Volume VII, Issue II
November 2025
Available online at https://www.instabrightgazette.com

reduction, load balancing, constraint satisfaction rates, and faculty satisfaction. We compared the results against traditional manual scheduling methods to confirm improvements in efficiency and fairness.

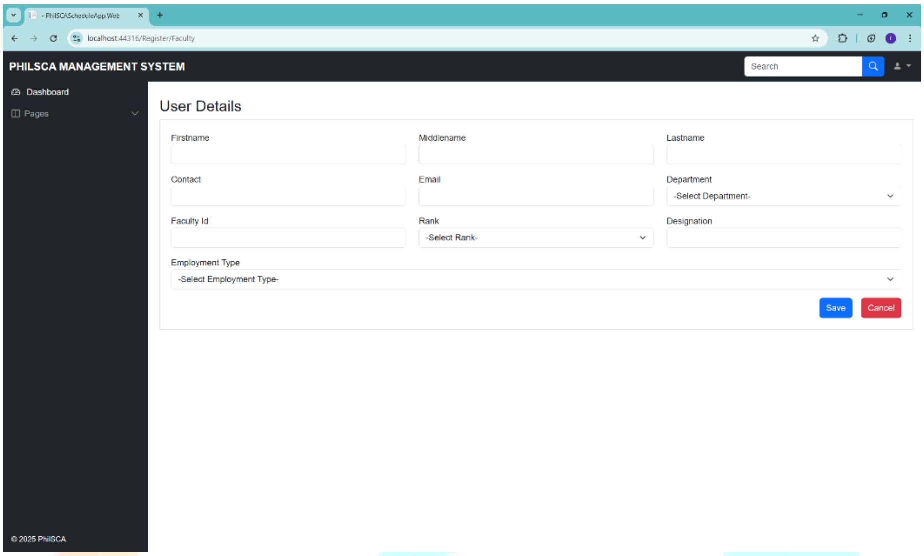

Fig. 1 Add Users

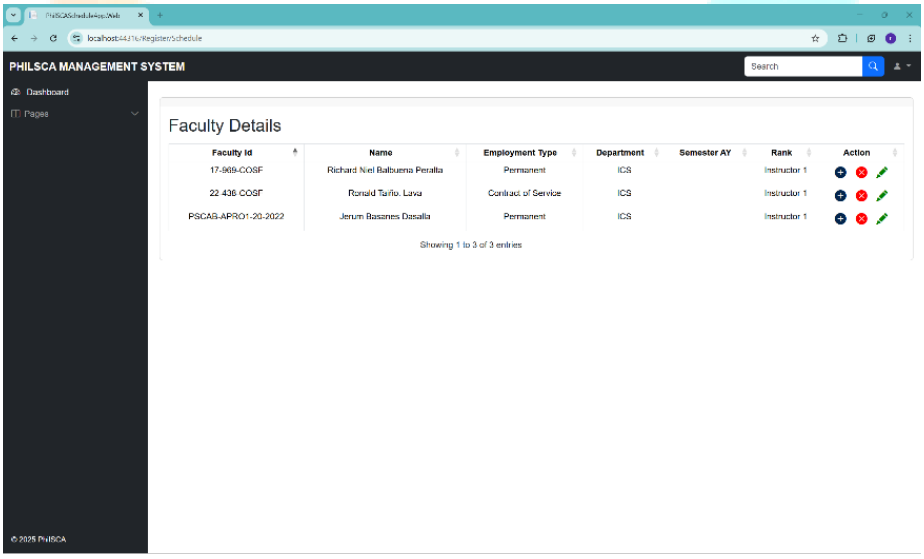

Fig. 2 Faculty Details

INSTABRIGHT e-GAZETTE
ISSN: 2704-3010
Volume VII, Issue II
November 2025
Available online at https://www.instabrightgazette.com

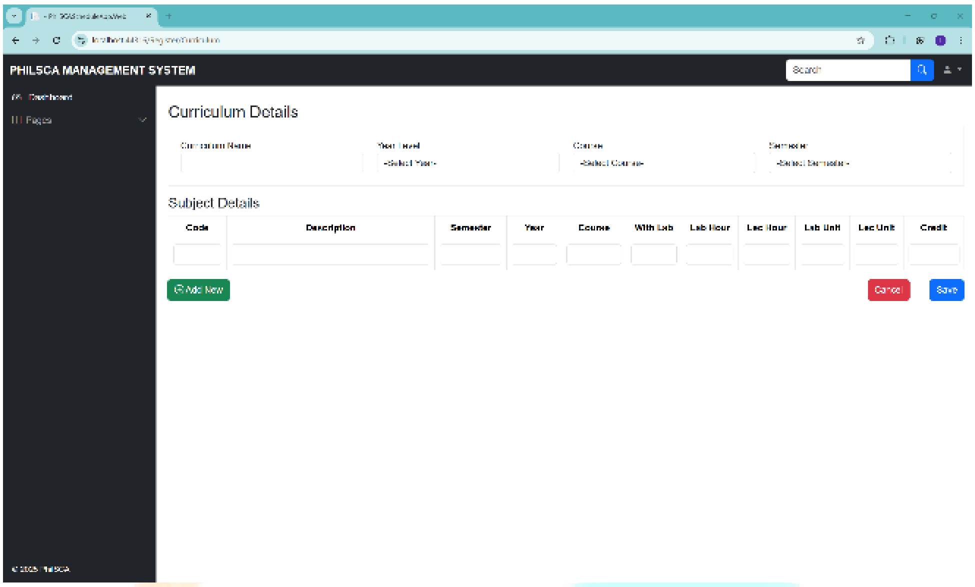

Fig. 3 Curriculum Details

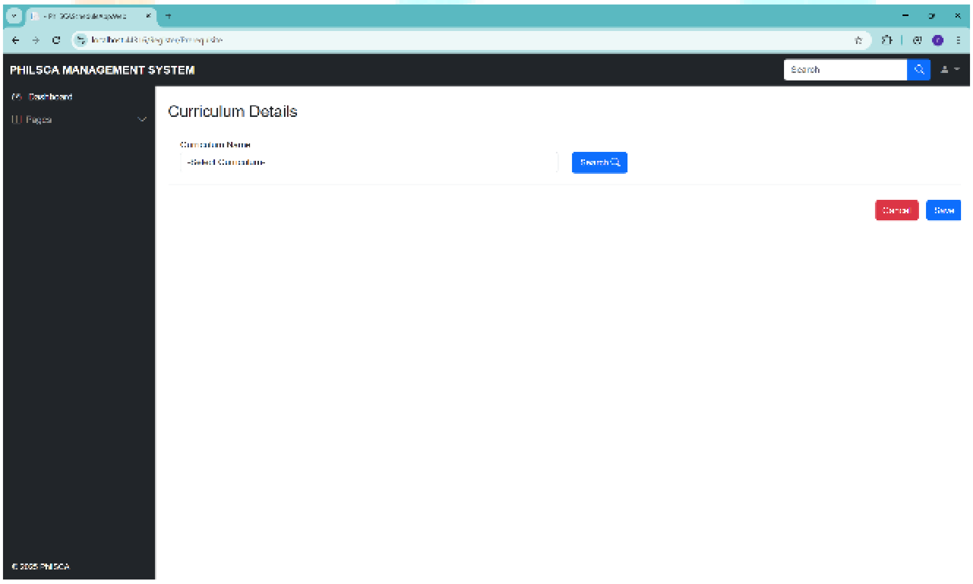

Fig. 4 Add Curriculum

INSTABRIGHT e-GAZETTE
ISSN: 2704-3010
Volume VII, Issue II
November 2025
Available online at https://www.instabrightgazette.com

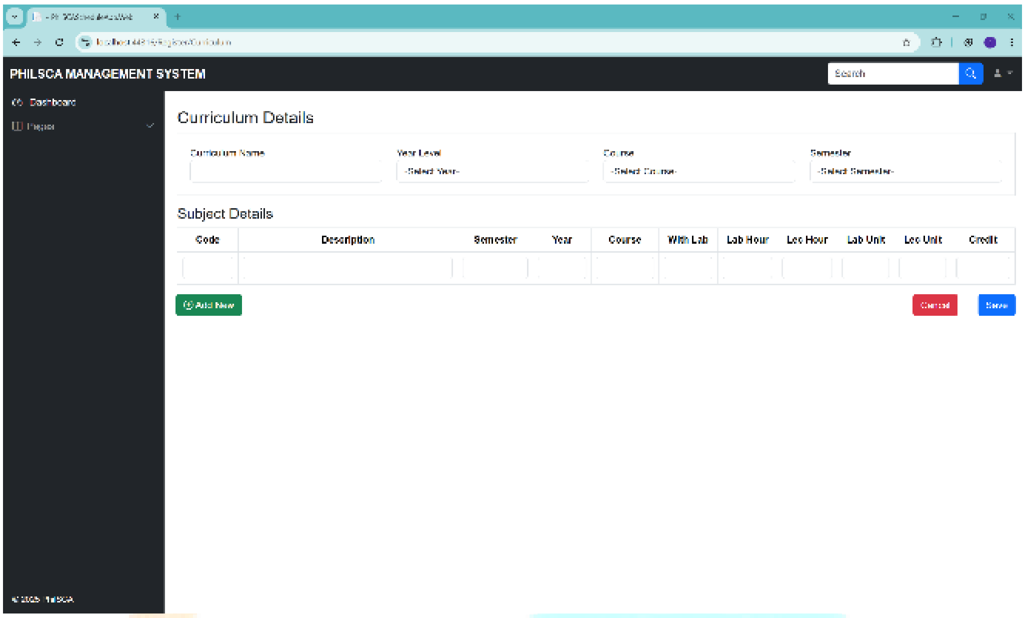

Fig. 5 View Curriculum

Finally, the maintenance phase suggests regular data updates, training the machine learning model periodically, and including faculty feedback to keep improving system accuracy and flexibility in changing academic environments.

RESULTS AND DISCUSSION

This section presents the main findings from the implementation and evaluation of the hybrid rule-based and machine learning faculty workload scheduling system. We used simulated datasets based on institutional records and faculty surveys to compare the hybrid model's performance with traditional manual and rule-based methods.

A. Conflict Reduction

Table I summarizes the number of scheduling conflicts encountered under three different scheduling approaches. The hybrid system significantly reduced conflicts compared to manual and rule-based systems.

INSTABRIGHT e-GAZETTE
ISSN: 2704-3010
Volume VII, Issue II
November 2025
Available online at https://www.instabrightgazette.com

Table-I

Comparison of Scheduling Conflicts Across Approaches

Scheduling Method	Number of Conflicts	Reduction (%)
Manual	55	—
Rule-Based Only	28	49.1%
Hybrid System	10	81.8%

As shown in Table I, the hybrid model reduced scheduling conflicts by **81.8%** compared to manual scheduling and by **64.3%** compared to the rule-based method. This improvement is attributed to the predictive ability of the machine learning component in identifying potential conflicts and assigning workloads accordingly.

B. Workload Balance

Faculty workload balance was measured using the variance in teaching hours among faculty members. A lower variance indicates a more equitable distribution.

Table-II

Variance in Faculty Teaching Hours

Scheduling Method	Average Hours	Variance (hrs^2)
Manual	15.8	6.5
Rule-Based Only	16.2	3.7
Hybrid System	15.9	2.1

The hybrid system achieved the lowest variance in teaching hours (**2.1 hrs^2**), demonstrating its effectiveness in producing a more balanced and fair workload distribution. The rule-based method performed better than manual scheduling but lacked the adaptability to minimize variance further.

C. Preference Satisfaction

Faculty preferences for start–end times were collected via survey and used to assess how well the system met individual time preferences.

Table-III

Faculty Preference Satisfaction Rate

Scheduling Method	Satisfaction Rate (%)
Manual	62%
Rule-Based Only	76%
Hybrid System	91%

With a **91%** satisfaction rate, the hybrid model significantly outperformed both manual and rule-based methods. This result indicates that integrating machine learning into the scheduling process enhances the system's responsiveness to faculty preferences.

D. Prediction Accuracy

The supervised machine learning model was evaluated on its ability to accurately predict faculty workload requirements and class assignments based on historical data.

Table-IV

Machine Learning Model Performance

Metric	Value (%)
Prediction Accuracy	89
Precision	87
Recall	90
F1-Score	88.5

The model achieved an overall **accuracy of 89%**, indicating its reliability in predicting faculty workload patterns and assisting in dynamic workload distribution. The relatively high precision and recall scores confirm the model's stability in handling different input scenarios.

INSTABRIGHT e-GAZETTE
ISSN: 2704-3010
Volume VII, Issue II
November 2025
Available online at https://www.instabrightgazette.com

CONCLUSION

This study presented a hybrid rule-based and machine learning approach for optimizing faculty workload distribution, specifically addressing start–end time constraints, fairness, and scheduling efficiency. By integrating deterministic rule-based logic for handling hard institutional constraints with a machine learning model trained on historical workload data and faculty preferences, the system effectively bridged the gap between policy compliance and adaptive scheduling.

The results demonstrated significant improvements across multiple performance metrics. Scheduling conflicts were reduced by over 80%, workload variance among faculty decreased notably, and time preference satisfaction reached 91%. Moreover, the machine learning model exhibited high predictive accuracy, enhancing the system's capability to generate balanced and preference-aware schedules.

The findings confirm that hybrid systems offer practical advantages over manual and rule-based-only approaches. The combined use of automation, rules, and predictive analytics ensures that institutional policies are respected while adapting to individual faculty needs—an essential factor in improving faculty morale and operational productivity.

Future implementations are encouraged to include real-time feedback mechanisms, continual data updates, and retraining cycles for the machine learning component. Further research should explore the scalability of the model across larger institutions and the integration of more complex soft constraints, such as research hours, administrative roles, and preferred teaching sequences.

INSTABRIGHT e-GAZETTE
ISSN: 2704-3010
Volume VII, Issue II
November 2025
Available online at https://www.instabrightgazette.com

REFERENCES

[1] H. L. Johnson et al., "Redefining faculty workload metrics: A data-driven approach," J. Prof. Nurs., vol. 55, pp. 112–118, 2024. [Online]. Available: https://doi.org/10.1016/j.profnurs.2024.08.006

[2] P. Ludwig-Beymer et al., "Evaluation of a new faculty teaching workload model," Nurse Educator, vol. 48, no. 6, pp. 326–331, 2023. [Online]. Available: https://doi.org/10.1097/NNE.0000000000001447

[3] E. Perez Ortega, M. M. dela Torre Ortega, and D. I. Brigoli, "Online class scheduling and faculty loading system within a decision support framework," JPAIR Institutional Research, vol. 6, no. 1, pp. 61–77, 2015. [Online]. Available: https://doi.org/10.7719/irj.v6i1.36339

[4] [Authors not specified], "Faculty loading system capstone project document," CapstoneGuide.com, 2020.

[5] R. S. Guirre and B. R. B. De Alba, "Development of a computerized faculty loading, room utilization, subject, and student scheduling system for Bulacan Polytechnic College," [Online].

[6] [Authors not specified], "A proposed faculty loading guide framework for research subjects in the Senior High School in the Philippines," Int. J. Curric. Instr., vol. 15, no. 1, pp. 178–191, 2023.

[7] H. Okahana et al., "Undoing disparities in faculty workloads: A randomized trial experiment," PLoS One, vol. 13, no. 12, p. e0207316, 2018. [Online]. Available: https://doi.org/10.1371/journal.pone.0207316

INSTABRIGHT e-GAZETTE
ISSN: 2704-3010
Volume VII, Issue II
November 2025
Available online at https://www.instabrightgazette.com

[8] B. S. Campanilla et al., "Development of a Web-Based Pre-Loading System for Faculty in a University," IAMURE Int. J. Math. Eng. Technol., vol. 13, 2016.

[9] L. D. Austero et al., "Optimizing faculty workloads and room utilization using heuristically enhanced whale optimization algorithm," Int. J. Adv. Comput. Sci. Appl., vol. 13, no. 11, pp. 97–104, 2022. [Online]. Available: https://doi.org/10.14569/IJACSA.2022.0131112

[10] G. Keh and M. Sarmiento, "Automated class scheduling system for Aemilianum College, Inc.," Glob. Sci. J., vol. 13, no. 2, pp. 299–307, 2025. [Online]. Available: https://www.globalscientificjournal.com/researchpaper/AUTOMATED_CLASS_SCHEDULING_SYSTEM