Optimized Nurse Scheduling and Patient Admission Prediction Using Machine Learning

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Abstract - *Efficient nurse scheduling is vital for hospital management to optimize workforce utilization and maintain fairness. This paper presents a Hybrid Ensemble Model, combining Genetic Algorithm (GA), Ant Colony Optimization (ACO), Particle Swarm Optimization (PSO), Simulated Annealing (SA), Reinforcement Learning (RL), and forecasting models (XGBoost/LSTM) to generate adaptive schedules. We also introduce a Modified PDE-ODE model for patient demand forecasting using neural networks with time series features. The combined system enhances scheduling efficiency, balances workloads, and improves responsiveness to dynamic patient needs.*

Key Words: Nurse Scheduling Problem, Patient Demand Forecasting, Ensemble Method, Reinforcement Learning, Workforce Optimization, Hospital Management, Machine Learning

1.INTRODUCTION

Efficient nurse scheduling is a critical aspect of hospital management, aiming to balance workforce constraints, patient care demands, and employee satisfaction. The Nurse Scheduling Problem (NSP) is a combinatorial optimization challenge that requires assigning nurses to shifts while adhering to complex hard and soft constraints. Traditional scheduling methods, such as rule-based algorithms and standalone metaheuristics like Genetic Algorithm (GA) or Reinforcement Learning (RL), often struggle with real-time adaptability, fairness, and workload balancing. These limitations can lead to inefficient scheduling, overburdened staff, and compromised patient care.

To overcome these challenges, we introduce a Hybrid Ensemble Model for Nurse Scheduling that combines metaheuristic optimization with reinforcement learning and forecasting techniques. Our model employs a multi-phase pipeline:

- Global Search Phase: Utilizes GA and Ant Colony Optimization (ACO) to generate diverse initial schedules and reinforce promising solutions.
- Local Refinement Phase: Leverages Particle Swarm Optimization (PSO) and Simulated Annealing (SA) to fine-tune the schedule, minimizing constraint violations and balancing workloads.
- Dynamic Adjustment Phase: Uses reinforcement learning (RL) and a forecasting model (XGBoost/LSTM) to adapt schedules based on real-time changes, such as nurse absences or fluctuating patient demand.

In addition to scheduling optimization, this study incorporates a Predictive Demand Forecasting Model powered by Partial Differential Equations (PDE) and Ordinary Differential Equations (ODE). This model uses PyTorch and deep learning techniques to predict future hospital admissions, enabling more accurate staffing decisions. The PDE-ODE framework enhances the scheduling system by providing reliable patient demand predictions, which improves resource allocation and reduces staff overburdening.

The PDE-ODE model processes historical hospital admissions data with lag features, moving averages, and temporal indicators (e.g., day of the year, week of the year). It employs a neural network architecture with batch normalization, dropout layers, and early stopping to optimize accuracy and prevent overfitting. The model achieves reliable R^2 and RMSE scores, demonstrating its effectiveness in capturing complex temporal patterns. By integrating this forecasting model into the scheduling system, the proposed solution dynamically adjusts nurse allocations based on predicted patient influx, leading to better resource management and improved patient care.

This integrated framework enhances the fairness, adaptability, and efficiency of nurse scheduling systems in dynamic hospital environments, offering a comprehensive solution for workforce optimization and demand forecasting.

2. LITERATURE SURVEY

Efficient nurse scheduling is vital for hospital management to balance staffing constraints and ensure quality patient care. Traditional scheduling methods often fail to handle dynamic workforce needs, leading to inefficiencies. Recent studies highlight the effectiveness of hybrid metaheuristic models and time series forecasting in improving schedule adaptability and demand prediction. By integrating optimization techniques with patient demand forecasting (PDE-ODE models), hospitals can enhance resource planning and staff allocation, ensuring better operational efficiency.

1) Gawali et al. (2022): Proposed a Partial Differential Equation (PDE) and Ordinary Differential Equation (ODE)-based model for solving dynamic systems and forecasting problems. The study integrates finite difference methods and neural network approximations to enhance the accuracy of time-dependent predictions. The model demonstrates effectiveness in time series forecasting and solving complex mathematical models, making it suitable for applications in scientific computing and resource management.

2) Ikura et al. (1988): Proposed a nurse scheduling system using combinatorial optimization techniques to allocate nurses efficiently across multiple shifts. The study introduces a mathematical programming model that optimizes shift distribution while minimizing overtime and ensuring fairness. The model demonstrates effectiveness in handling staffing constraints and improving hospital workforce management.

3) Brucker et al. (2010): Introduced a nurse scheduling model using integer programming and constraint satisfaction techniques. The study focuses on optimizing shift assignments while considering workload distribution, fairness, and labor regulations. The model demonstrates improved efficiency in handling large-scale scheduling problems and reducing constraint violations in hospital workforce management.

4) Williams et al. (2023): Developed a "Machine Learning-Based Resource Management System" to optimize laboratory sample transportation within healthcare settings. Using historical data and predictive modeling, the system schedules transport for lab samples, reducing unnecessary emergency visits. The simulation demonstrated potential cost savings of 5% to 14% annually.

5) Shao et al. (2023): Introduced an efficient combination of Genetic Algorithm and Particle Swarm Optimization for scheduling data-intensive tasks in heterogeneous cloud computing. The study formulates task scheduling as a binary non-linear programming problem with optimization objectives of maximizing accepted tasks and overall resource utilization. The proposed hybrid heuristic algorithm (PGSAO) integrates genetic algorithm strategies into particle swarm optimization to improve efficiency and avoid local optima. Experimental results demonstrate improved scheduling performance in heterogeneous cloud environments.

6) Nagayoshi & Tamaki (2023): Proposed a dynamic nurse scheduling system using reinforcement learning to handle sudden nurse absences. The study enhances traditional nurse scheduling by incorporating real-time adjustments through reinforcement learning, ensuring optimized work schedules while considering various constraints. The method improves practical usability by revising schedules dynamically, increasing efficiency in hospital workforce management.

3. PROPOSED SYSTEM

1.1 Problem Statement

Effective hospital workforce management requires both optimized nurse scheduling and accurate patient demand prediction to ensure efficient resource allocation and high-quality patient care. However, existing scheduling methods often struggle with constraint violations, workload imbalances, and computational inefficiencies. Simultaneously, traditional demand forecasting approaches fail to capture real-time variations, leading to staffing mismatches and operational inefficiencies.

This paper proposes a Hybrid Ensemble Model that integrates optimization techniques (GA, ACO, PSO, SA, RL) for nurse scheduling with mathematical modeling (ODEs, PDEs) for patient demand forecasting. The scheduling framework leverages global and local search methods to generate balanced and constraint-compliant nurse assignments, while reinforcement learning and predictive modeling dynamically adjust schedules based on real-time patient trends. The patient demand prediction model employs differential equations to model hospital admission dynamics, capturing seasonal trends, disease progression, and emergency fluctuations.

By bridging scheduling optimization with data-driven demand forecasting, this approach minimizes constraint violations, balances workloads, and ensures real-time adaptability. The result is an efficient, scalable, and intelligent scheduling system that enhances hospital resource management while maintaining optimal patient care.

1.2 Data Collection

The datasets used in this study were collected from various sources, providing insights into nurse scheduling and hospital admissions.

Nurse Scheduling Dataset:
This dataset contains records of nurse work schedules, including shift allocations, working hours, and fairness metrics. Key attributes include:
Nurse ID: Unique identifier for each nurse.
Shift Type: Different shift categories (morning, evening, night).

Working Hours: Total hours assigned per nurse per week.
Penalty Scores: Constraints violations impacting fairness and efficiency.
Fairness Metrics: Measures such as standard deviation and coefficient of variation.

This dataset is essential for evaluating workload balance, fairness, and efficiency in nurse scheduling.

Hospital Admissions Dataset:
This dataset contains hospital admission records, tracking various patient-related details. Key attributes include:
Patient ID: Unique identifier for each patient.
Admission Date: Date of hospital admission.
Diagnosis: Primary reason for hospital admission.
Length of Stay: Duration of hospitalization.
Treatment Type: Category of medical treatment received.

The dataset provides critical insights into hospital resource utilization, patient care trends, and admission patterns.

1.3 Models

1) Optimized Hospital Nurse Scheduling Model: The model incorporates constraints such as shift limits, consecutive workhour restrictions, and skill-based assignments to ensure optimal scheduling. By utilizing integer linear programming (ILP) or heuristic-based approaches, the system minimizes scheduling conflicts, reduces nurse fatigue, and improves overall efficiency. The implementation demonstrates scalability for larger datasets and provides near-optimal solutions within reasonable computational time. This approach significantly enhances workforce management by automating complex scheduling tasks and improving operational efficiency in hospital settings.

Constraint Formulation: Nurse scheduling is governed by hard constraints, which must always be satisfied, and soft constraints, which should be minimized to improve overall schedule quality.
Hard Constraints (Strict Rules)
• Maximum Work Hours Per Nurse: Each nurse is restricted to a maximum number of work hours to prevent excessive workload and fatigue.

$$\sum_{t \in T} H(n,t) \leq MaxHours(n), \quad \forall n \in N \tag{1}$$

where H(n, t) is a binary function that returns 1 if nurse n is assigned to time slot t, otherwise 0, and *MaxHours(n)* is the maximum permissible working hours for nurse n.

• Shift Coverage Requirement: Every shift must be adequately staffed according to patient demand.

$$\sum_{n \in N} S(n,s) \geq Demand(s), \quad \forall s \in S \tag{2}$$

where S(n, s) indicates whether nurse n is assigned to shift s, and Demand(s) represents the minimum required nurses for shift s.

• Skill-Based Assignment: Only nurses possessing the required skills should be assigned to specialized shifts.

$$\sum_{n \in N} SkillMatch(n,s) \geq MinSkill(s), \quad \forall s \in S \tag{3}$$

where *SkillMatch(n, s)* is 1 if nurse n has the required skills for shift s, otherwise 0, and *MinSkill(s)* is the minimum number of qualified nurses needed for shift s.

Soft Constraints (Preferences and Optimizations)
Soft constraints help improve scheduling quality but can be
violated at a penalty cost.

• Nurse Shift Preferences: Nurses should be assigned to preferred shifts whenever possible.

$$P_{shift} = \sum_{n \in N, s \in S} Pref(n,s) \times (1 - S(n,s)) \tag{4}$$

where P ref (n, s) is 1 if nurse n prefers shift s, otherwise 0. A lower P_{shift} value indicates better preference satisfaction.

• Consecutive Shift Violations: Nurses should not be scheduled for consecutive shifts without sufficient rest.

$$P_{consec} = \sum_{n \in N} \sum_{t=1}^{T-1} V(n,t) \times H(n,t) \times H(n,t+1) \tag{5}$$

where V (n, t) represents a penalty factor for consecutive shift violations.

• Minimizing Last-Minute Changes: Frequent changes to a nurse's schedule should be avoided.

$$P_{change} = \sum_{n \in N, t \in T} LMC(n,t) \times |S_{new}(n,t) - S_{old}(n,t)| \tag{6}$$

where LM C(n, t) is higher if changes occur close to shift time.

Model Architecture Overview: Our proposed Hybrid Ensemble Model for Nurse Scheduling is a multi-layered optimization framework that integrates diverse techniques to address the complex constraints inherent in nurse scheduling.

The architecture is organized into four main layers:

a) Global Search – Initial Schedule Generation:: In this phase, the model leverages a Genetic Algorithm (GA) to generate a diverse population of candidate schedules. Each candidate is represented as a chromosome encoding nurse-shift assignments. To refine these initial solutions, Ant Colony Optimization (ACO) is incorporated. Here, a pheromone matrix is maintained, reinforcing promising assignments and guiding the search towards high-quality schedules that strictly satisfy hard constraints such as maximum work hours and required shift coverage.

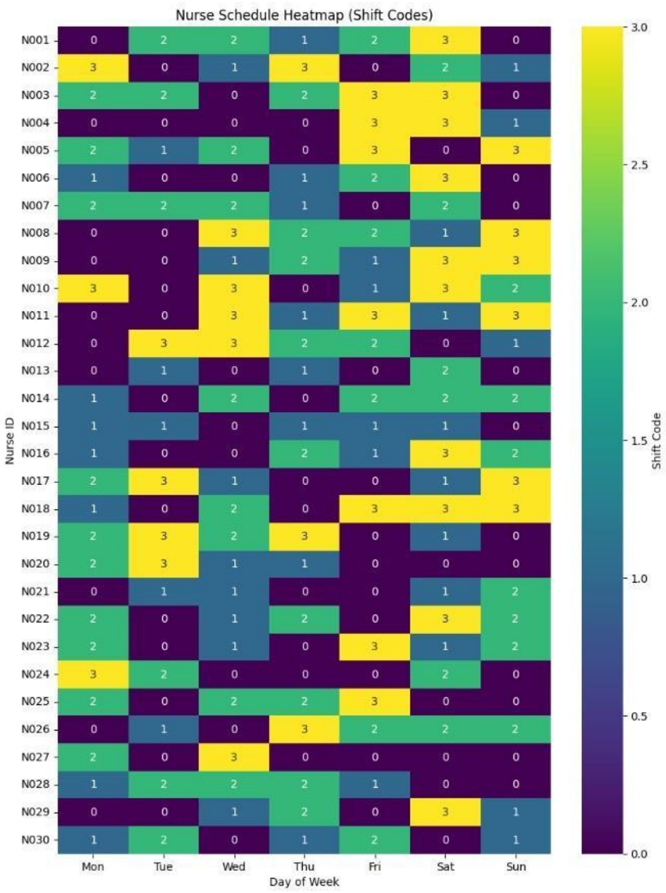

Fig. 1. Heatmap Diagram

b) Local Refinement – Fine-Tuning:: Once an initial schedule is available, Particle Swarm Optimization (PSO) is applied. In PSO, each schedule is treated as a particle whose position (i.e., the assignment of shifts) is iteratively adjusted based on its own best performance and the global best solution found. Complementing this, Simulated Annealing (SA) introduces controlled randomness through a temperature parameter, allowing the model to escape local optima and further reduce violations—particularly soft constraints related to shift preferences and workload balance.

c) Dynamic Adaptation – Real-Time Adjustments:: To ensure adaptability, a Reinforcement Learning (RL) agent is integrated. The RL component views the scheduling problem as a Markov Decision Process, where the state comprises the

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Average working hours per nurse: 36.27 hours/week
Standard deviation of working hours: 6.44
Number of nurses exceeding max working hours: 0
Fairness metric (Coefficient of Variation): 0.18
Total penalty (lower is better): 6.83
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Fig. 2. Schedule Metrics Diagram

current schedule and nurse availability, and actions represent possible adjustments. The RL agent learns to make fine-grained changes that minimize an overall penalty function, dynamically adapting to real-time events such as nurse absences.

d) Forecasting – Proactive Demand Prediction:: Finally, forecasting models based on XGBoost and LSTM predict future patient inflow and nurse absenteeism. These predictions inform schedule adjustments, ensuring that the model can proactively allocate resources to meet anticipated demand, thereby improving overall scheduling stability.

This hybrid structure integrates global search, local refinement, dynamic adaptation, and forecasting, resulting in a robust scheduling system that effectively minimizes constraint violations and achieves a fair workload distribution.

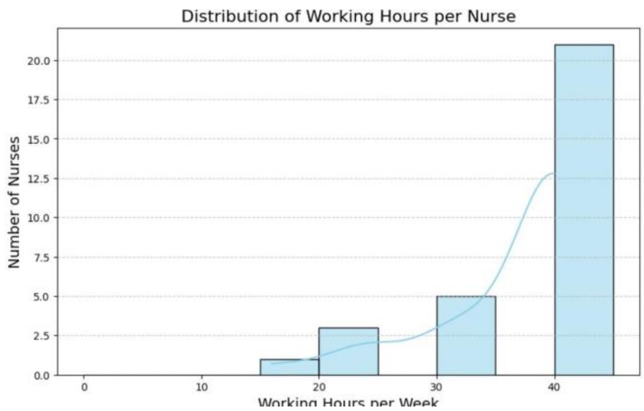

Fig. 3. Distribution of Working Hours per Nurse Diagram

Experimental Results: a) Hybrid Ensemble Model Results:

The experiments were conducted on Google Colab, which had the following specifications:

- Processor: Intel Xeon CPU @ 2.20GHz
- Memory: Approximately 12GB RAM
- GPU: NVIDIA Tesla T4 (enabled for GPU-accelerated

tasks such as RL training and LSTM forecasting)
The experiments with the hybrid ensemble model yielded the following outcomes:
• The optimized schedule generated by the hybrid model successfully minimized both hard and soft constraint violations.
• The model converged rapidly to a solution with a near-zero violation count, ensuring that all critical constraints were fully met.
• Visualizations from our experiments (e.g., workload heatmaps and violation trend graphs) clearly indicate that the hybrid model achieves balanced nurse assignments with fewer last-minute adjustments.

b) Pure GA Model Results: For comparison, we implemented a baseline Pure GA Model using only the Genetic Algorithm without the additional layers (ACO, PSO, SA, RL, and forecasting). The Pure GA model generated schedules that:

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--- Pure GA Schedule Metrics ---
Average working hours per nurse: 35.20 hours/week
Standard deviation of working hours: 6.73
Coefficient of Variation (fairness metric): 0.19
Total penalty (lower is better): 8.73
Number of nurses exceeding max working hours: 0
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Fig. 4. Pure GA Schedule Metrics Diagram

• Met the hard constraints but incurred higher soft constraint violations.
• Demonstrated a less uniform workload distribution, with a slightly lower average working hour allocation and greater variability.
• Required more iterations to converge and resulted in a higher overall penalty score.

c) Comparative Results and Performance Metrics Analysis: The performance of the hybrid ensemble model was quanti-
tatively compared with that of the Pure GA model using the
following metrics:

• Average Working Hours:
  – Hybrid Ensemble: 36.27 hrs
  – Pure GA: 35.2 hrs

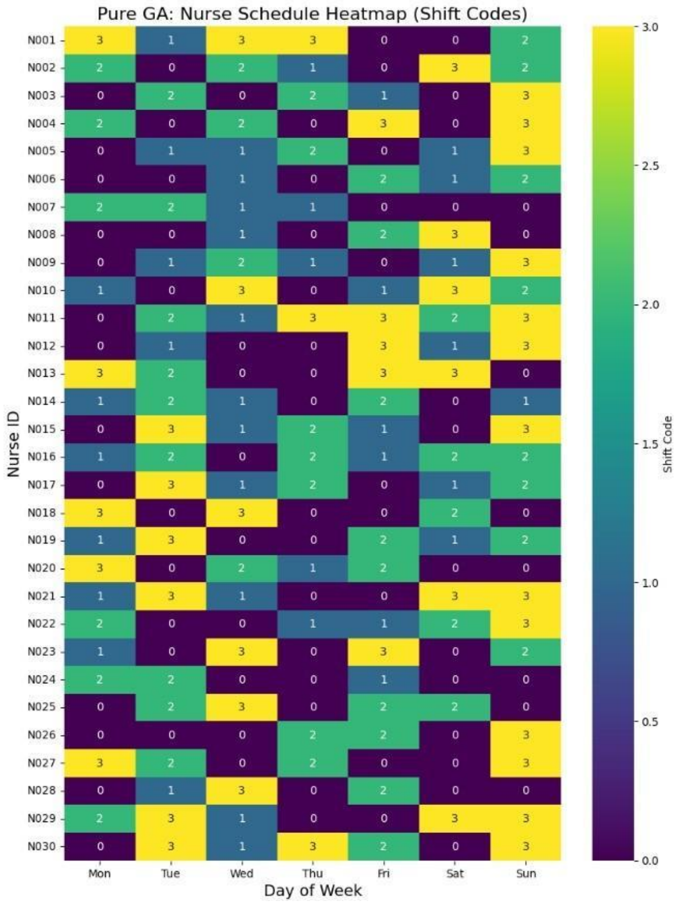

Fig. 5. Heatmap diagram

The hybrid model distributes shifts more evenly while maintaining practical scheduling norms.
• Standard Deviation of Workload:
  – Hybrid Ensemble: 6.44 hrs
  – Pure GA: 6.73 hrs

A lower standard deviation in the hybrid model indicates a more uniform workload across nurses.
• Coefficient of Variation (FI):
  – Hybrid Ensemble: 0.1777
  – Pure GA: 0.1911

This metric further confirms that the hybrid approach yields more consistent shift assignments.
• Total Penalty Score:
  – Hybrid Ensemble: 6.83
  – Pure GA: 8.73

A lower penalty in the hybrid model reflects superior constraint adherence and fewer scheduling conflicts.
• Violation count:
  – Both models achieved a zero violation count for hard constraints, ensuring full regulatory compliance.

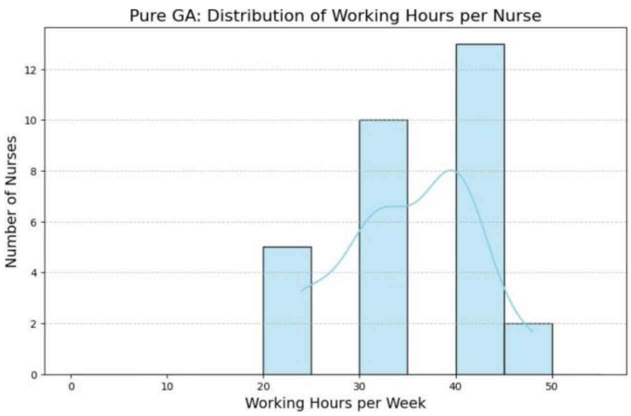

Fig. 6. Distribution of Working Hours per Nurse Diagram

The experimental results clearly indicate that our Hybrid Ensemble Model outperforms the Pure GA Model on several fronts:

• Constraint Adherence: The hybrid model significantly reduces both hard and soft constraint violations, as evidenced by the lower total penalty score.

• Workload Balance: Metrics such as the standard deviation and coefficient of variation demonstrate that the hybrid approach achieves a more balanced distribution of shifts among nurses.

• Optimization Efficiency: The hybrid model converges faster and exhibits improved schedule stability with fewer last-minute changes, making it more suitable for real-time scheduling scenarios.

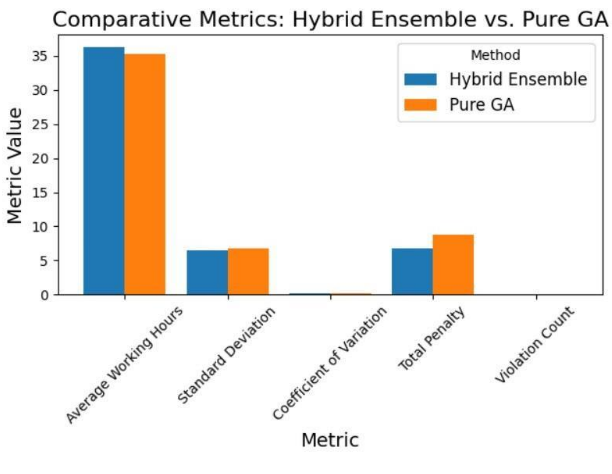

Fig. 7. Hybrid Ensemble vs. Pure GA Comparative Metrics Diagram

2) Optimized PDE-ODE Model for Hospital Admission Prediction:

To enhance the forecasting of hospital admissions, we propose an Optimized Partial Differential Equation-Ordinary Differential Equation (PDE-ODE) model. This model leverages deep learning techniques while drawing inspiration from differential equations to effectively capture temporal patterns in admission data.

Feature Engineering To improve predictive accuracy, the dataset was processed to include essential time-dependent features:

• Time Index (t_{idx}): Number of days since the first record.

• Cyclical Features: Day of the year (d_y), month (m), and weekday (w).

• Moving Average (M A7): A 7-day rolling mean to smooth out fluctuations.

• Lag Features (Li): Past 14 days of hospital admissions used as inputs:

$$L_i = A_{t-i}, \quad i \in [1, 14] \tag{7}$$

Neural Network Architecture The proposed model is structured as follows:

1) Input layer with n features:

$$X = \{t_{idx}, d_y, m, w, MA_7, L_1, L_2, ..., L_{14}\} \tag{8}$$

2) Fully connected hidden layers:

$$h_1 = ReLU(W_1X + b_1) \tag{9}$$

$$h_2 = ReLU(W_2h_1 + b_2) \tag{10}$$

3) Dropout regularization (p = 0.3) applied to hidden layers to mitigate overfitting.

4) Output layer predicts hospital admissions At:

$$\hat{A}_t = W_oh_2 + b_o \tag{11}$$

Training and Optimization The model is trained using the AdamW optimizer with weight decay regularization:

$$\theta_{t+1} = \theta_t - \alpha \left(\frac{\nabla L(\theta_t)}{\sqrt{v_t} + \epsilon} + \lambda\theta_t \right) \tag{12}$$

where λ is the weight decay factor, α is the learning rate, and v_t is the moment estimate.

Evaluation and Forecasting The model performance is assessed using:

• Coefficient of Determination (R2):

$$R^2 = 1 - \frac{\sum(A_i - \hat{A}_i)^2}{\sum(A_i - \bar{A})^2} \tag{13}$$

Result: Final R^2 Score: 0.7919 Upon training, the model is utilized to predict hospital admissions for the next 7 days by extrapolating the time series and using the latest known values.

	date	Predicted Admissions
0	2025-02-18	32.825806
1	2025-02-19	33.183334
2	2025-02-20	33.540863
3	2025-02-21	33.895321
4	2025-02-22	34.241081
5	2025-02-23	34.587292
6	2025-02-24	32.641083

Fig. 8. Future 7 Days Prediction Diagram

4. CONCLUSIONS

In summary, our ensemble approach leads to a more robust, efficient, and adaptive nurse scheduling system compared to a Pure GA-based model. Additionally, the incorporation of the PDE-ODE model further enhances the predictive accuracy and adaptability of the system. The PDE-ODE model effectively captures temporal dependencies and handles complex, dynamic variations in hospital admissions. This hybrid modeling approach improves the accuracy of nurse scheduling by accounting for both short-term fluctuations and long-term trends, resulting in more reliable and efficient workforce planning.

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BIOGRAPHIES

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