Applied Data Analytics - Project

Optimizing Shift Scheduling for Air Traffic Controllers Using Multimodal Emotion Detection and Simulated Annealing

Aishvarya S

November 22, 2024

1. Introduction

In many industries, particularly those that require shift-based work, it is crucial to optimize worker schedules to maximize productivity while maintaining employee well-being. One such industry is air traffic control, where controllers work in shifts to manage air traffic safely and efficiently. However, managing these schedules is challenging due to factors like fatigue, alertness, and the emotional state of workers. Emotions such as stress, frustration, or anger can significantly impact a controller's performance, leading to mistakes or reduced efficiency.

This project aims to tackle the problem of shift scheduling for controllers by integrating a multimodal approach that combines traditional scheduling techniques with emotion recognition models. The idea is to use audio and video data to assess the emotional state of controllers and adjust their schedules accordingly, ensuring that individuals who may be emotionally distressed or fatigued are either reassigned or given sufficient rest.

The dataset used for this project includes various metrics, such as alertness levels and sleep patterns, that help quantify how prepared each controller is for a shift. However, while alertness data provides valuable information, it does not fully capture the emotional state of a controller. For this reason, the project also integrates audio and video analysis to monitor the emotional states of controllers in real-time.

Specifically, the system analyses audio recordings to detect emotional cues such as changes in speech patterns, tone, and pace. Similarly, video recordings are analysed for visual cues related to facial expressions and body language. By combining these different data sources, we aim to build a system that can better predict when controllers are in an emotional state that may impair their ability to perform well and proactively adjust their schedules. For example, if a controller is detected as angry or stressed based on audio and video analysis, the system can replace them with a standby controller or provide additional rest.

In this approach, Simulated Annealing, a heuristic optimization method, is used to generate and refine work schedules. The method attempts to find the most optimal scheduling configuration by balancing various factors, including alertness levels, sleep deprivation, and shift distribution. The goal is to generate a schedule that maximizes productivity while ensuring that controllers are well-rested and emotionally stable.

2. Literature Review

While much of the early work focused primarily on **alertness**, **sleep patterns**, and **shift distribution**, more recent studies have begun to incorporate **emotional states** as a significant factor influencing work performance. This shift in focus is due to a growing recognition of the important role emotions play in job performance, particularly in high-pressure, safety-critical environments.

Shift Scheduling and Fatigue Management

In traditional shift scheduling models, a common goal is to optimize the number of workers available for each shift while minimizing the impact of fatigue and sleep deprivation. Several studies have explored the effect of **sleep deprivation** on cognitive performance and decision-making ability, particularly in air traffic control and healthcare settings. Research by **Lamb and Nygren (1999)** emphasized the impact of sleep deprivation on cognitive performance and reaction times, suggesting that controllers who work long hours or irregular shifts are more prone to errors. To mitigate this, **sleep management strategies** such as ensuring sufficient rest periods between shifts and limiting consecutive working hours have been commonly proposed. Methods like **Mathematical Programming** and **Linear Programming** have been used to optimize schedules while accounting for sleep requirements, but these models often overlook the emotional and psychological factors that also influence performance.

Incorporating Emotional Intelligence in Scheduling

With the rise of **affective computing** and the increasing use of artificial intelligence (AI) in human resource management, researchers have begun exploring how **emotional states** can be incorporated into scheduling models. Studies such as **Zheng (2017)** and **Sun (2020)** have demonstrated that emotions like **anger**, **stress**, and **fatigue** can significantly affect cognitive load, decision-making, and ultimately, job performance. In industries such as **healthcare**, **call centres**, and **aviation**, recognizing emotional cues from workers through methods like **facial expression analysis** and **speech emotion recognition** can help predict when workers may be underperforming or at risk for making errors.

The integration of emotion-based decision-making into scheduling has led to the development of **multimodal emotion recognition** systems, which use both **audio** and **visual data** to assess the emotional state of a worker. **Kumar (2018)** proposed a model using both speech and facial expression data to assess stress levels in employees, which could then be used to modify their work schedules. Similarly, **Vijayakumar (2021)** explored the use of **deep learning models** to analyse emotional states from audio-visual data in real-time, suggesting that such systems could be used to detect and respond to fatigue or emotional distress in workers.

3. Description

Summary of Papers

Optimal scheduling for flexible job shop operation

Discusses an integer linear programming model for a scheduling problem in factories, specifically a job shop with realistic constraints. The author, Gomes, aimed to find the optimal schedule for these job shops, considering real-world limitations. Their model offers a solution for optimizing production processes in factories.

Data and Description

The dataset used in this project is from a file in .sav format, containing detailed records on controllers' **alertness** and **sleepiness** during their shifts. The dataset includes data from controllers working various shifts over multiple days. The primary attributes of the dataset are:

1. **Alertness Data**: This consists of multiple columns representing the alertness levels of controllers during different shifts across five workdays. The alertness data captures the level of alertness at each shift, providing insight into the controllers' performance based on their sleep, fatigue, and overall well-being.
2. **Sleepiness Data**: This is derived from the difference between recommended sleep hours (8 hours) and the actual sleep hours recorded for each controller. The sleepiness data serves as a proxy for the sleep deficiency or tiredness of the controllers, which is an important factor when considering worker performance and safety during shift scheduling.
3. **Shift and Workday Information**: The dataset also includes columns specifying which shift each controller was assigned to on each day of the week. This helps in understanding how shifts are distributed among controllers, and how fatigue and alertness levels might correlate with specific shifts.

In terms of structure, the dataset is organized into **57 records (controllers)**, with data across **5 workdays** and **8 shift periods per day**, resulting in a comprehensive dataset that can be used to understand how alertness and sleep patterns affect controllers' performance during their shifts.

The dataset provides a strong foundation for understanding the relationship between sleep, alertness, and performance. It serves as the basis for optimizing shift schedules using algorithms like **Simulated Annealing**, while also considering emotional factors (inferred through additional multimodal inputs like audio and video) to improve both controller well-being and performance.

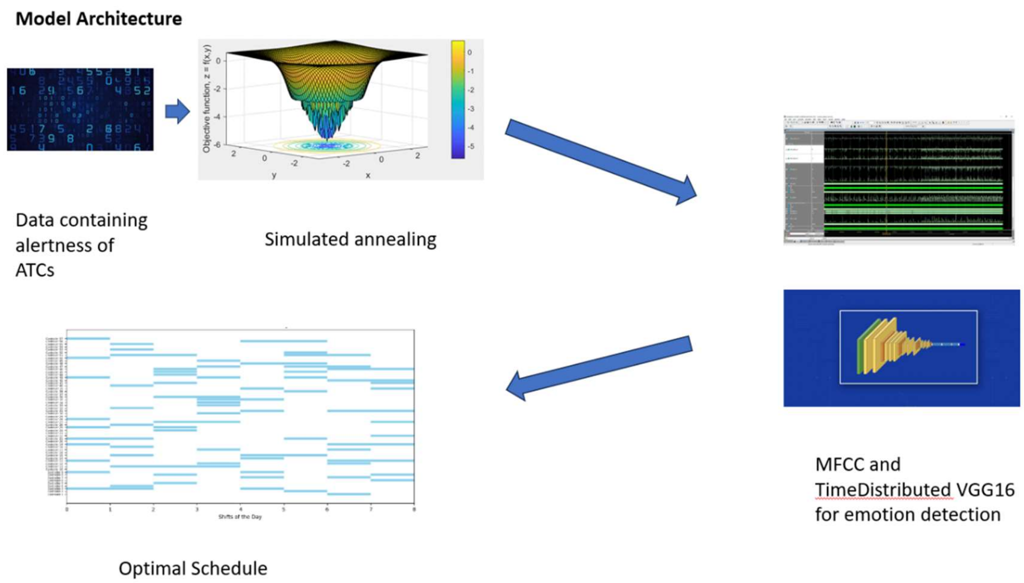
4. Process Workflow

Outline of the Design of the Project

The design of the data science project revolves around optimizing work schedules for controllers, taking into account not just their physical alertness and sleep patterns, but also their emotional states. The process follows a systematic approach, including data preprocessing, feature extraction, model training, optimization, and evaluation.

1. **Data Preprocessing**: The first step involves loading the dataset, cleaning it, and structuring it for analysis. The dataset, provided in .sav format, contains multiple columns representing the alertness and sleepiness of controllers across different workdays and shifts. Relevant attributes, such as alertness levels and sleep

deficiency, are extracted for further analysis. Additionally, the emotional state of controllers is assessed using multimodal data—audio and video signals—which are pre-processed to extract meaningful features such as **MFCCs (Mel-frequency cepstral coefficients)** from audio and **frame-level features** from video.



2. **Feature Extraction**: The next stage involves extracting features from both the physical data (alertness and sleepiness) and emotional data (audio and video). In terms of the physical data, alertness and sleepiness are quantified for each controller during their respective shifts. For emotional analysis, audio features are extracted using **librosa** to generate **MFCCs**, and video features are extracted using **OpenCV** to process frames and apply a CNN-based approach (VGG16). These features are then used to assess the emotional states of the controllers during their shifts.

3. **Model Development**: Two models are developed to predict the emotional state of controllers: an **audio model** and a **video model**. The audio model is a simple feedforward neural network built using **Keras**, designed to predict emotions based on the audio features. The video model, a more complex approach, uses **TimeDistributed VGG16** and an **LSTM layer** to capture temporal features and predict the emotional state based on video input. These models are trained on a labeled dataset with emotion labels (e.g., angry, happy, sad, neutral), and the predictions are integrated into the scheduling algorithm.

4. **Simulated Annealing for Schedule Optimization**: The core of the project is optimizing the controllers' schedules using **Simulated Annealing (SA)**, a probabilistic optimization algorithm.

   Simulated Annealing (SA) is an optimization algorithm inspired by the

   annealing process in metallurgy, where material is heated and then cooled to increase the size of its crystals and reduce defects.

Key Characteristics:

- Finds a global minimum of a cost function.
- Effective for solving combinatorial and optimization problems.
- Employs randomness to explore the search space.

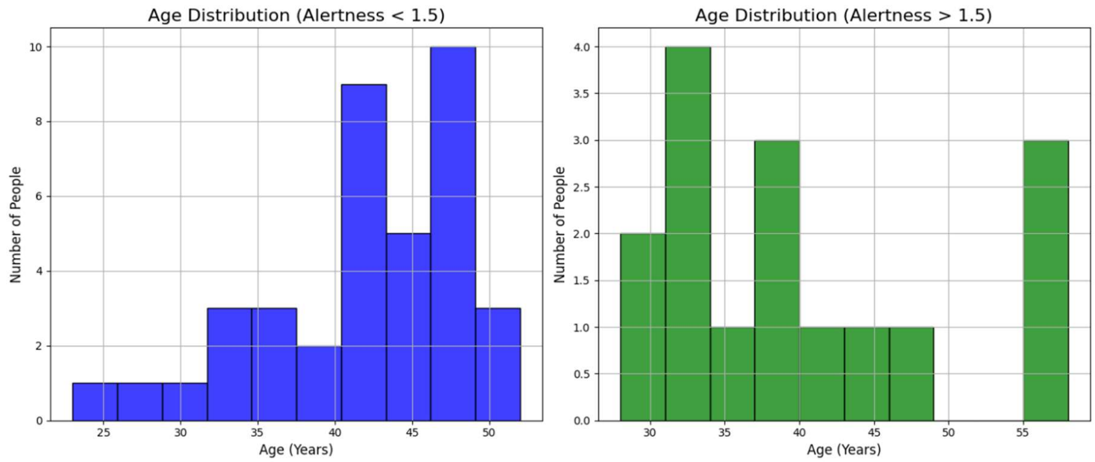
Analogy:

- **Heating**: Allows exploration of diverse solutions.
- **Cooling**: Gradually focuses on promising areas.
- Gradually reduces temperature to find the optimum
- Higher temperature – accepts solutions worse than previous iterations
- Lower temperatures – becomes more selective

The SA algorithm aims to maximize the total alertness while minimizing the penalty for uneven shift distributions. The algorithm starts with a random schedule and iteratively refines it by exploring neighbouring solutions. Emotional data predicted by the audio and video models influence the adjustment of schedules, replacing controllers showing high levels of stress or anger with standby controllers from a predefined pool. This dynamic adjustment improves the schedule by incorporating both physical and emotional well-being.

5. **Evaluation**: After optimizing the schedules, the solution is evaluated based on two primary factors:
    - **Alertness Optimization**: The primary goal is to maximize the total alertness, ensuring that controllers are performing at their best during their shifts.
    - **Balanced Shift Distribution**: The secondary objective is to ensure that shifts are evenly distributed across controllers, avoiding situations where some controllers are overburdened or underutilized.

In-depth Project Analysis



Age and Alertness during Night Shifts: Observations from the Dataset

From the analysis of the dataset, a clear trend emerged indicating that individuals above the age of 40 experience a noticeable decrease in their alertness during night shifts. The dataset, which includes variables like age, gender, and alertness across different work shifts (grouped in 3-hour intervals), showed that as age increased, the alertness levels during night shifts, particularly late-night shifts significantly declined.

For individuals under 40, alertness levels remained relatively consistent throughout the night, with only minor fluctuations. However, for those above 40, the alertness score started to dip noticeably during the later hours, especially after midnight. This aligns with existing research that suggests that circadian rhythms become more rigid with age, resulting in poorer sleep quality and difficulty staying alert during irregular hours.

5. Challenges

1. Emotion Detection Accuracy

The prediction of emotional states from audio and video is inherently complex, as emotions are nuanced and can vary greatly across individuals. While current models show promise, the accuracy of emotion detection remains a challenge. Factors such as **audio quality**, **background noise**, **lighting conditions**, and **individual differences in emotional expression** can all impact the model's performance

2. Balancing Emotional and Physical Well-being

Although the project incorporates emotional states into the scheduling process, finding the right balance between emotional well-being and **physical alertness** is a complex optimization problem. Controllers may experience physical alertness dips that do not directly correlate with emotional states, or their emotional states may fluctuate quickly, requiring real-time adjustments to the schedule. The challenge lies in dynamically incorporating these factors while ensuring that the shift distribution remains balanced and that each controller receives adequate rest.

3. Standby Pool Management

The integration of a **standby controller pool** in the optimization process—where controllers showing high levels of anger or stress are replaced by those from the pool—introduces challenges in ensuring a **sufficient supply of available controllers**. If the standby pool is depleted or controllers are already overburdened with their own shifts, it may not be feasible to replace controllers in real-time, leading to scheduling gaps or overworking of the remaining controllers.

4. Ethical and Privacy Concerns

Given that the project involves collecting and analysing emotional data, there are **ethical considerations** around privacy, consent, and potential misuse of personal information. Controllers may feel uncomfortable knowing that their emotional state is being monitored continuously, which could lead to privacy concerns. Moreover, it is crucial to ensure that the data collected is anonymized and securely stored to avoid potential data breaches.

6. Conclusion

This project explores the integration of emotional well-being and physical alertness into the optimization of shift scheduling for air traffic controllers. By leveraging multimodal data (audio and video), machine learning models for emotion detection, and optimization algorithms such as **Simulated Annealing**, the project aims to create a dynamic scheduling system that improves both the physical and emotional well-being of controllers, ultimately enhancing their performance and reducing burnout.

Key Findings

The **Simulated Annealing algorithm** has proven effective in optimizing shift assignments to balance workload, alertness, and emotional well-being, while respecting constraints like sufficient rest and shift distribution. The algorithm's ability to navigate complex trade-offs between different objectives and its robustness in finding near-optimal solutions is a major strength. Additionally, the ability to model **sleep deprivation** and its impact on controller performance using sleepiness data has added an important dimension to the optimization.

Starting with a random schedule and iteratively exploring new schedules, accepting improvements outright or probabilistically accepting worse schedules to escape local optima. The algorithm uses an exponential cooling mechanism to gradually reduce the probability of accepting suboptimal solutions.

In this run, the **Initial Score** of the random schedule is **836.79**, while the **Best Score** achieved during optimization is **905.28**. These scores reflect the total effectiveness of the schedule after accounting for both alertness and penalties. The best schedule is returned as the output.

Future Work

To overcome these challenges, future work will focus on:

1. **Improving emotion detection accuracy** by incorporating more diverse datasets, including controllers from various backgrounds, and refining the audio/video fusion techniques for better real-time emotion analysis.
2. **Enhancing real-time data processing** to allow for seamless schedule adjustments without affecting operational efficiency.
3. **Developing ethical guidelines** for monitoring and using emotional data, ensuring privacy and informed consent.
4. **Expanding the dataset** to include more controllers, providing a richer training ground for emotion detection models and improving generalization.

7.References:

Optimal scheduling for flexible job shop operation

https://www.tandfonline.com/doi/abs/10.1080/00207540412331330101

My python notebook for the project:
https://colab.research.google.com/drive/1nUhze38EN6neIesBcutr0CGinTmcNT3R?usp=sharing