Workforce Planning: Developing Smart AI-driven Schedule Optimizers

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1 Introduction

In the face of dynamic market conditions and evolving business requirements, workforce planning has become more critical than ever before. The conventional manual approaches to scheduling often fall short of addressing the complexities of modern workplaces. Organizations are increasingly recognizing the need for intelligent, adaptive systems to optimize workforce schedules. This project aims to bridge this gap by leveraging the power of AI to create Smart Schedule Optimizers capable of handling scheduling challenges, ensuring optimal resource utilization and enhancing overall operational efficiency.

The primary contribution of this project is the development of AI-driven Schedule Optimizers that go beyond traditional scheduling algorithms. These optimizers will be equipped with machine learning capabilities to analyze historical data, predict future demand patterns, and dynamically adjust schedules to align with organizational goals. The proposed system aims to enhance workforce efficiency, reduce operational costs, and improve employee satisfaction by generating schedules that balance workload, skill requirements, and individual preferences.

These SSO (Smart Schedule Optimizers) are designed to be adaptable to various industries and organizational structures. The customization capabilities of the system allow for an integration into diverse work environments, catering to the unique scheduling challenges each organization may face. We employ a methodology in developing the SSO that involves : leveraging machine learning algorithms, predictive analytics, and optimization techniques. The system will learn from historical scheduling data, adapt to changing patterns, and continuously refine its recommendations. It will also explore the integration of real-time data sources and feedback loops to ensure the adaptability of the optimizer in dynamic work environments.

Furthermore, a comprehensive validation process will be implemented to assess the performance and reliability of the developed SSO. This includes testing the system against different scenarios (fed to us by open access data sources), evaluating its ability to handle unprecedented challenges. We introduce a new approach to the scheduling of work hours and breaks using AI algorithms, promising an adaptable solution to enhance the whole of workforce planning across different industries.

Keywords: Workforce Planning, Scheduling Optimizers, Machine Learning, Artificial Intelligence, Heuristic Algorithms

2 State of the art

A study conducted by McKinsey & Company (a global management consulting firm founded in 1926, that offers professional services to corporations, governments, and other organizations) showed the impact of smart scheduling on the planning measurements, including job delays and false starts.

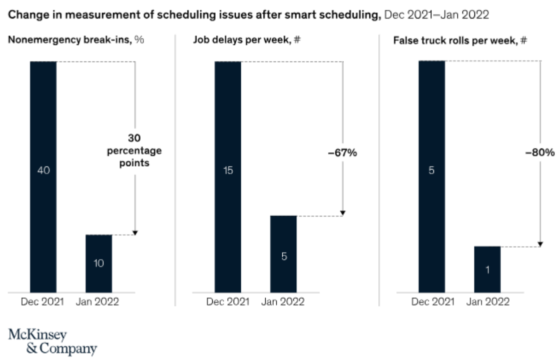

Figure 1: Study conducted by McKinsey & Company showing the impact of smart scheduling on the planning measurements.

There was also an increase in productivity of the operators.

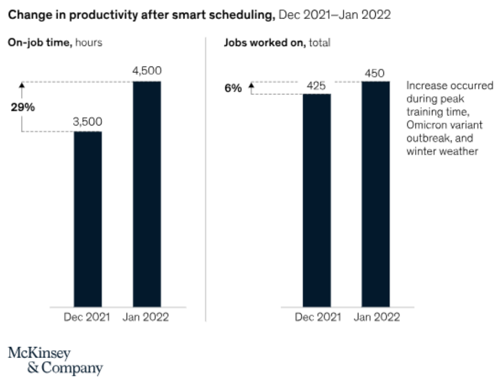

Figure 2: Study conducted by McKinsey & Company showing the impact of smart scheduling on productivity.

In what follows, we present a state of art of 5 different scientific works (Indexed in Scopus) that fall into the field of work hours scheduling. We describe briefly the methodologies and approaches they used, as well as the results they got. We structure our descriptions following two main points: How the works are related to the OSH (Occupational Health and Safety) and their approach to digitalizing the problem using AI.

2.1 Reliability Engineering using Bayesian Network

This work [1] is published in a paper entitled "Predicting human reliability based on probabilistic mission completion time using Bayesian Network". It emphasizes the critical role of human factors in task completion, highlighting how physical and mental demands, alongside variables like learning, forgetting, fatigue, and stress, significantly influence task performance and completion times. It also notes the inherent uncertainties in performance prediction, as traditional methods often fall short in accounting for these complex, fluctuating human elements. The paper focuses on the dynamics of learning and forgetting, acknowledging that repetition enhances performance while interruptions or task switching can lead to performance degradation. Furthermore, it addresses the cumulative impact of fatigue, which gradually decreases a worker's ability to maintain optimal performance levels, and the effect of stress, triggered by external factors, on both efficiency and the quality of performance. A key observation is the variability in performance among different workers, manifested in their varying initial performance levels, rates of learning and forgetting, accumulation of fatigue and stress, and their responses to diverse task environments. This comprehensive perspective underscores the multifaceted nature of human performance in task completion.

This work's approach to digitalizing work-hours scheduling is through the use of Bayesian models to for predicting a mission duration, t_N, consisting of N tasks of i types.

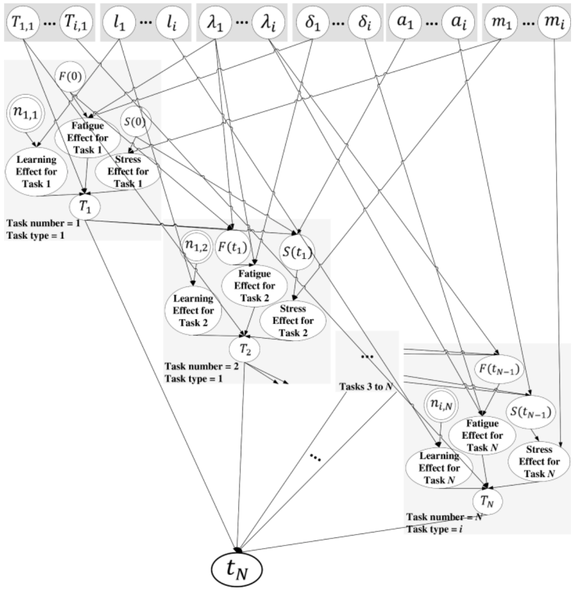

Figure 3: Bayesian model structure.

2.2 Fatigue, personnel scheduling and operations

This study [6] focuses on how operational research literature measures and models fatigue, its impact on operational performance, and ways to mitigate these effects. The authors explore the relationship of fatigue literature with work-rest scheduling, shift scheduling, multitasking, ergonomics, deterioration scheduling, and occupational health and safety. The paper discusses both objective and subjective methods of assessing fatigue. This includes online operator monitoring, quantification of accumulated fatigue, performance-based monitoring, and subjective measures like fatigue assessment scales.

The research highlights the role of operational research in work-rest scheduling and shift scheduling, focusing on how these scheduling decisions impact fatigue. It reviews mathematical programming, queueing, heuristic, and empirical methodologies applied to fatigue study in personnel scheduling. It discusses main operational applications where fatigue is a significant issue, including manufacturing, construction, transportation, hospitals, and services. It examines how fatigue arises and is addressed differently in these sectors. The study does not integrate directly the implementations of AI solutions but examines different ways in which data is sourced, used, and results are implemented in fatigue-related operational research. It highlights the importance of real data usage and practical implementation of the research findings. The authors promise future works by identifying several important research directions for operational research to promote its broader and more effective use in mitigating the effects of fatigue on operational performance.

2.3 An efficient constructive method for an effective staff scheduling

In addressing the critical challenge of effective staff scheduling in software development management, this work [2] proposes a new approach that takes advantage of artificial intelligence techniques to streamline the workforce planning process. Unlike most existing work that primarily focuses on constructing working schedules based on a given workforce size, this research focuses on a different issue – determining whether the existing manpower can meet scheduling requirements before delving into the scheduling process. Recognizing the potential time complexities associated with traditional methods such as network flow theory or genetic algorithms, the authors introduce a constructive method designed to derive the minimum staff number for three scheduling problem variants in linear running time. This method not only establishes a theoretical lower bound for computation time complexity but also substantiates its correctness. We show the structure of the new constructive method in Figure 4.

The integration of AI, particularly through a comparison with a genetic algorithm, showcases the efficiency and effectiveness of the proposed method in generating schedules that meet diverse constraints, thereby contributing to more intelligent and resource-optimal staff scheduling in software development. The study extends the application of AI beyond conventional task assignment or resource allocation in software engineering, emphasizing the role of intelligent staff scheduling in achieving cost and time savings during software development.

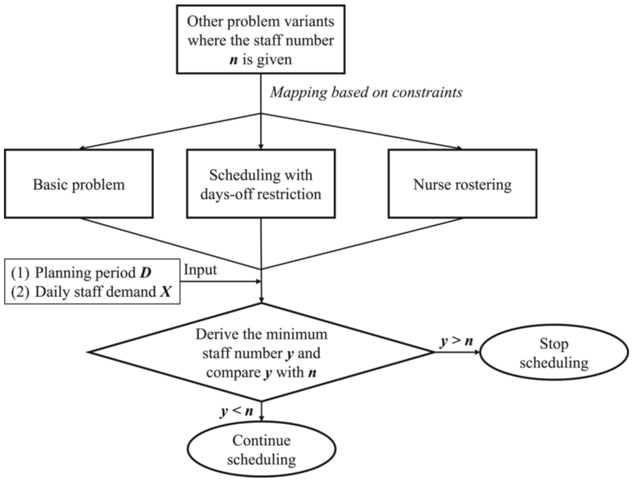

Figure 4: Workflow of using the minimum staff number as a sentinel for staff scheduling.

2.4 Optimizing the rest breaks configurations using HRA-based model

This study [3] aims to develop a model that identifies the optimal rest break schedules in work environments to ensure the psychophysical recovery of operators, thereby enhancing overall performance and reducing errors. The research presents a model named the Simulator for Human Error Probability Analysis (SHERPA), which uses HRA methods to predict human error probability (HEP) in different industrial contexts. It considers factors like the task at hand, performance shaping factors (PSFs), and the duration of work.

Rest Breaks Configuration Simulation: A significant function of SHERPA is simulating different rest break schedules. It analyzes the entire work shift, identifying moments of highest operator unreliability, and manages breaks. The integration of Artificial Intelligence in this research paper is primarily through the development and application of the Simulator for Human Error Probability Analysis (SHERPA). This AI-based simulation model leverages various AI techniques to optimize rest break schedules in human-intensive working environments relying on:

∗ Predictive Analysis: SHERPA uses AI algorithms to predict human error probability (HEP) based on a range of performance shaping factors (PSFs) and the specific tasks being performed. This predictive capability is a key AI application, allowing the model to anticipate potential errors before they occur.

∗ Simulation and Modeling: The model simulates different work environments and rest break scenarios. AI algorithms help in modeling complex work systems and their interaction with human factors, providing insights into optimal scheduling.

∗ Optimization Algorithms: SHERPA applies economic optimization algorithms to determine the best times for rest breaks. These algorithms assess the balance between productivity (time spent working) and the risk of errors (and their potential costs), aiming to find the most efficient schedule. This is an example of AI's capability in decision-making and optimization.

∗ Data-Driven Decision Making: The application of AI in SHERPA involves processing and analyzing large volumes of data related to work patterns, error rates, and operator performance.

AI algorithms are used to extract meaningful insights from this data, which are crucial for effective decision-making.

∗ Adaptability and Flexibility: The AI model is designed to adapt to various industrial contexts, suggesting that it can learn and adjust to different settings, which is a core characteristic of AI systems.

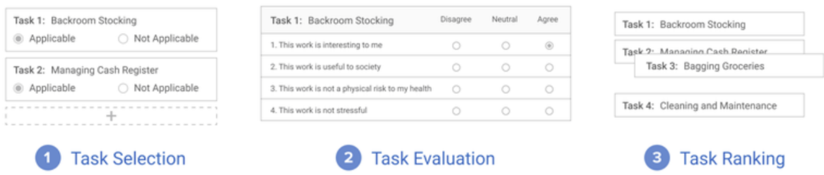

Figure 5: Ranking-based elicitation for task preference model. 1) The worker selects relevant tasks. 2) The worker provides inputs on their evaluations for each task. 3) The worker ranks the tasks according to their preferences.

2.5 Elicitation Methods for Worker Well-Being Models

This study [5] aims to create models that capture worker well-being, taking into account individual preferences regarding work and working conditions, and managerial fairness. These models are intended to inform and optimize algorithmic management systems in workplaces. The researchers propose two primary models:

∗ Work Preference Model: Captures individual preferences about work and working conditions.

∗ Managerial Fairness Model: Relates to perceptions of fair resource allocation among multiple workers.

The paper introduces methods to elicit these models from workers, leveraging pairwise comparisons and rankings. These methods are participatory, allowing workers to actively contribute to the modeling of their well-being. They worked on a case study integrating Artificial Intelligence and relying on algorithmic work scheduling. It was conducted with 25 shift workers and 3 managers. This involved using AI to analyze the data collected from the elicitation methods, thereby creating personalized well-being models. The results were promising: Workers expressed unique work preferences and more uniform managerial fairness models. The participatory elicitation methods helped workers discover their preferences and provided them with a sense of empowerment.

This study provides initial evidence for enabling participatory algorithmic management focused on worker well-being. Broader Implications: The research contributes to the field of human-computer interaction and algorithmic work management, offering a method centered on worker well-being. It highlights the potential of AI and participatory methods to improve work environments and worker satisfaction. Furthermore, It discusses the complexities of integrating these models into actual work environments, considering organizational contexts and the balance between worker preferences and operational efficiency.

2.6 Opportunistic Scheduling for Productive Laziness

This paper [4] introduces the concept of "productive laziness," which emphasizes the importance of balancing work and rest for workers to ensure long-term success and well-being in AI-mediated workforce management systems. The research proposes a distributed Computational Productive Laziness (CPL) approach, which uses AI to recommend personalized work-rest schedules. This approach takes into account local data about a worker's capabilities and situational factors to optimize rest periods while maintaining high productivity.Also, a novel Work-Rest Index is derived, expressing the interplay among situational factors, worker performance, system-level preferences, and personal preferences. This index helps in dynamically determining the timing and amount of work and rest a worker should undertake. The study aligns with the IEEE Ethically Aligned Design guideline, prioritizing worker well-being in scheduling algorithms. It aims to achieve a balance between efficiency and ethical considerations in workforce management.

About the experimental evaluation: The paper includes extensive experiments based on a real-world dataset of over 5,000 workers. These experiments demonstrate that the CPL approach enables workers to spend a significant portion of their time resting while still completing a high percentage of tasks efficiently. The CPL method was shown to significantly outperform alternative approaches, consistently achieving superlinear collective productivity. This means that the collective productivity achieved is larger than the sum of individual productivity, indicating an efficient use of workforce resources. This opens avenues for designing workforce management systems that promote a balance between work and rest, ultimately enhancing worker well-being and system productivity. Future research aims to testbed CPL in crowdsourcing platforms to reach out to more diverse users and study how to improve the approach in various behavior patterns.

3 Pipeline of the project

"A survey conducted by McKinsey found that 69% of manufacturing companies have already implemented AI in at least one part of their production process, with production scheduling being a key focus area. In another study by Deloitte, 76% of manufacturers reported that AI technologies have significantly improved their production scheduling accuracy and reduced production downtime." These surveys shed light on the scheduling of production in the manufacturing field, but what about workforce planning? What if the same work could be better distributed amongst the team by offloading peaks to underloaded co-workers? Our aim consists in optimizing the operators' work-hours through the use of Artificial Intelligence. We go into details of the methodologies and frameworks that will be used in this project.

3.1 Methodology

The methodology that we will rely on will be executed following multiple steps:

→ Identify Machine Learning algorithms and Heuristic algorithms used in the optimization of the the workforce planning.

→ Formulating the objective function for the algorithms.

→ Gather or generate artificial data containing information about employees and their work schedules.

→ Implement algorithms and generate initial solutions.

→ Evaluate algorithms and compare results.

3.2 Algorithms and Frameworks

3.2.1 Machine Learning Algorithms

Machine Learning algorithms can solve two of the main problems in workforce planning:

1. Job-to-work-center allocation: In some cases, the allocation of jobs to work centers must be decided before shifts can be optimized—for example, call centers where calls must be routed to different centers or field-force operations that must distribute jobs in different locations among a number of technician centers.

2. Dynamic Employee Shift Scheduling: In certain industries, particularly those with dynamic work environments such as healthcare, retail, or customer service, optimizing employee shifts involves intricate decisions. For instance, in healthcare, the allocation of healthcare professionals to specific shifts or departments must be carefully considered. Emergency departments might require different staffing levels during various times of the day, and the allocation of nurses, doctors, and support staff to these shifts is crucial. Similarly, in the retail sector, aligning employee shifts with peak shopping hours is essential for ensuring optimal customer service. Machine learning algorithms can analyze historical customer traffic data, predict future demand patterns, and optimize employee schedules accordingly. These models adapt to changing conditions, consider individual employee preferences, and aim to strike a balance between customer service excellence and efficient resource utilization.

Treating these modules can be done using the following ML algorithms: Mixed-Integer Linear Programming, Regression Models, Classification Models and finally Clustering.

3.2.2 Heuristic Algorithms

Like ML algorithms, Heuristic algorithms can also solve two of the main problems in workforce planning:

1. Demand and supply balancing: This is an integer programming problem in which the input is sub-daily demand and the output is required shifts. The module decides on the number of shifts needed and therefore addresses all or a portion of the demand (depending on the user's setting) while minimizing total costs.

2. Heuristic dispatching: Particularly if assigning jobs is complex, a heuristic approach can be successfully applied to dispatching problems. Some jobs might need to be prioritized, for example, or workers may have different competency levels. In these cases, heuristic optimization is the most powerful approach because it can apply all custom rules in a significantly flexible way. As a result of this approach's iterative nature, the user controls how optimal the response should be. That makes run times and required computational resources more flexible.

We will be using these specific heuristic algorithms to approach our problem: Genetic Algorithms, Simulated Annealing and Ant Colony Optimization.

3.2.3 Frameworks

We plan on using the following frameworks in the implementation of the algorithms cited previously: TensorFlow, Keras, Scikit-Learn and Pytorch.

3.3 Generating/ Gathering Artificial data

In order to compare the performances of the algorithms used in the optimization process, we will have to gather or generate artificial data. We will need data concerning information about employees, tasks, and operational requirements:

1. Employee Data:
   ∗ Availability: Information about when employees are available to work, considering factors such as working hours, part-time or full-time status, and days off.
   ∗ Skills and Qualifications: The skills, certifications, or qualifications possessed by each employee, which may influence their eligibility for specific tasks or roles.
   ∗ Preferences: Employee preferences for certain shifts, work locations, or types of tasks. Taking preferences into account can improve job satisfaction.

2. Task Data:
   ∗ Task Requirements: Information about the tasks that need to be completed, including skill requirements, duration, and deadlines.
   ∗ Task Dependencies: Relationships or dependencies between tasks, which may impact the order in which they should be scheduled.
   ∗ Priority: The priority or urgency associated with each task, helping to determine which tasks should be scheduled first.

3. Operational Requirements:
   ∗ Work Hours and Shifts: The organization's operating hours and the different shifts or time slots during which work can be scheduled.
   ∗ Legal and Regulatory Constraints: Compliance with labor laws, union agreements, or other regulatory constraints that dictate working hours, break times, and rest periods.
   ∗ Equipment and Resource Availability: If tasks require specific equipment or resources, scheduling must consider their availability.

4. Objectives and Constraints:
   ∗ Costs: Minimizing labor costs, overtime expenses, or penalties associated with non-compliance.
   ∗ Employee Preferences: Maximizing employee satisfaction by considering their preferences when assigning shifts or tasks.
   ∗ Workload Balancing: Distributing workload evenly among employees to prevent overloading some while under-utilizing others.

5. Dynamic Factors:
   ∗ Real-time Changes: Adapting to real-time changes in demand, unexpected absences, or emergencies that may require rescheduling.
   ∗ Seasonal Variations: Adjusting schedules to accommodate seasonal variations in workload or demand.

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