

A working week simulation approach to forecast personal well-being^{*}

Derek Groen¹[0000-0001-7463-3765], Shivank Khullar¹[0009-0004-7229-1887], Moqi Groen-Xu²[0000-0002-1337-8825], and Romyana Neykova¹[0000-0002-2755-7728]

¹ Department of Computer Science, Brunel University London, Kingston Lane, Uxbridge, UK

`derek.groen@brunel.ac.uk`

² School of Economics and Finance, Queen Mary University, London, UK.

Abstract. Billions of people work every week. Forecasting which tasks gets done in a working week is important because it could help workers understand (i) whether their workload is manageable and (ii) which task scheduling approach helps to maximize the amount of work done and/or minimize the negative consequences of unfinished work. Here we present a working week simulation prototype, R2, and showcase how it can be used to forecast the working week for three archetypical workers. We show that R2 forecasts are sensitive to different task loads, task scheduling strategies and different levels of emerging work complications. We also highlight how R2 supports a new type of validation setting, namely that of user self-validation, and discuss the advantages and drawbacks of this new validation approach. We provide R2 as an online platform to allow users to create their own worker profile and task lists, and believe the tool could serve as a starting point for more in-depth research efforts on user-centric working week modelling.

Keywords: simulation · task management · working week · simulation development approach.

1 Introduction

Many adults spend a non-negligible part of their weeks working. They have tasks that need to be done and face consequences, either in terms of professional or personal impact, when tasks are left unfinished [10]. The impact of the negative consequences depends on the perceived importance of the task, both from the perspective of the worker and of their possible superiors. The widespread prevalence of labour and its huge importance justifies the need to better understand how workers can operate effectively and how their well-being can be preserved. In this short paper we propose a simulation approach that focuses on modelling individual workers, and which is (perhaps unconventionally) intended to be eventually adopted by workers themselves. We sketch an early prototype of a workweek simulator, named R2, that may support workers, using their

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own assumptions, in forecasting their well-being and productivity at the end of a working week. The simulator requires workers to specify their workload in tasks, the expected impact on well-being for missing each task, and the expected availability and quality of working time throughout the week. Based on these provided assumptions, and a selected strategy for work task scheduling, the simulator then provides forecasts of which tasks are expected to be completed, and how much negative psychological events are expected from unfinished tasks and missed deadlines by the end of the working week.

1.1 Related work

The work we present concerns individual workers and their well-being. In recent years, worker well-being has become a more prominent topic, particularly in the case of workers with family duties [7] and workers in the healthcare sector [9]. As an example of empirical research on the topic, Hafenbrack and Vohs quantified empirically that mindfulness meditation had a positive effect on task motivation but not necessarily task performance [4]. We also identified a range of investigations on the topic of structuring the working week from a managerial perspective. These efforts range from exploring interventions that aim to boost productivity [1, 3] or well-being [11, 5] as well as guided design for job specifications [8]. However, a known complication for empirical studies on this topic is in terms of preserving the privacy of individual workers, and in terms of the reliability of externally reported worker well-being [2]. Within this paper we explore preset task scheduling strategies, which the user can manually select and apply. Although we focus mainly on the development approach of a user-centric working week simulation, it is also possible to focus on optimal task scheduling strategies. In this context the working week task allocation problem can be seen a variation of the job-shop problem [6], which has been extensively studied and for which many approaches exist [13, 12]. And yet, the working week simulation as we present is different to a classic job shop problem in important ways. It is both simpler in that it features a single processing unit (the worker) and more complicated in that it has a probability for new complication tasks to be spawned at any point.

2 Approach

Our code R2 essentially relies on a variation of Discrete-Event Simulation, where a single worker agent attempts to “do its work” during the workweek. Within the conceptual model, we specifically simulate how a single worker: (i) has time availability during the workweek, (ii) tackles pending tasks from their task list using this available time and a predefined scheduling strategy, (iii) experiences complications [additional tasks] in some cases when performing the base tasks and (iv) experiences negative psychological events towards the end of the workweek due to tasks being completed after their deadline or not at all.

We provide a high-level overview of our model and our simulation development approach (SDA) in Figure. 1. Here, the main unit of work in the model is a `Task`, which has the following attributes: duration [hours], priority [1-5 scale], `high_focus` [true or false], `cost_of_failure` [1-5 intensity scale], deadline [day of the week or None], `complication_probability` [chance of triggering the emergence of a complication task], `complication` [the task created when a complication occurs]. The main simulation kernel propagates the simulation in time, taking into account the worker profile and the chosen task scheduling strategy to choose and complete tasks. Once the workweek simulation has completed, R2 will provide a range of diagnostic outputs. These include: number of tasks completed in the week, number of complication spawned in the week (these are extra tasks that may arise at a preset probability when certain tasks are done), a completion score (which is a sum of `task.priority`² for each completed task), a negative impact score (which is a sum of `task.cost_of_failure`² for each incomplete task) and a list of negative events which contains the number of negative psychological events triggered during the workweek. The list of negative events is categorized across the five possible `cost_of_faillure` scores, which we informally label as: effortless (1), inconvenient (2), annoying (3), painful (4), and desperate (5).

To enable users to reproduce our results and perform their own experimentation, we provide R2 as a free to use web service for anyone³.

3 Exemplars

To illustrate the dynamics of R2 we provide simulation results for three exemplar workers: a manager, a software developer and a student. Although the exemplars are defined to be archetypal for these real-life roles, they are not intended to resemble real-world individuals. Below we provide a brief description for each exemplar, while the detailed input files can be found on Github⁴:

- Jordan is a manager overseeing various projects and teams. He has long working days with few periods dedicated to high-focus tasks and many meetings and administrative duties. Jordan’s week is characterized by multitasking across numerous short-duration tasks, from team reviews to strategic planning. His schedule is predominantly filled with meetings and manageable tasks, although he has a few high focus planning tasks.
- Alexa is a software developer working at a tech startup. Her involves coding, fixing bugs, and meeting with the team. Alexa’s week is filled with focused coding tasks, solving urgent problems, and participating in team meetings. She works typical office hours and does weekly sprint meetings early on the Monday morning.
- Mike, a university student, navigates a balanced academic week across 7 days, blending study with leisure and attending roughly 8 hours of lectures.

³ <https://ratrace.streamlit.app>

⁴ <https://www.github.com/djgroen/ratrace-inputs>

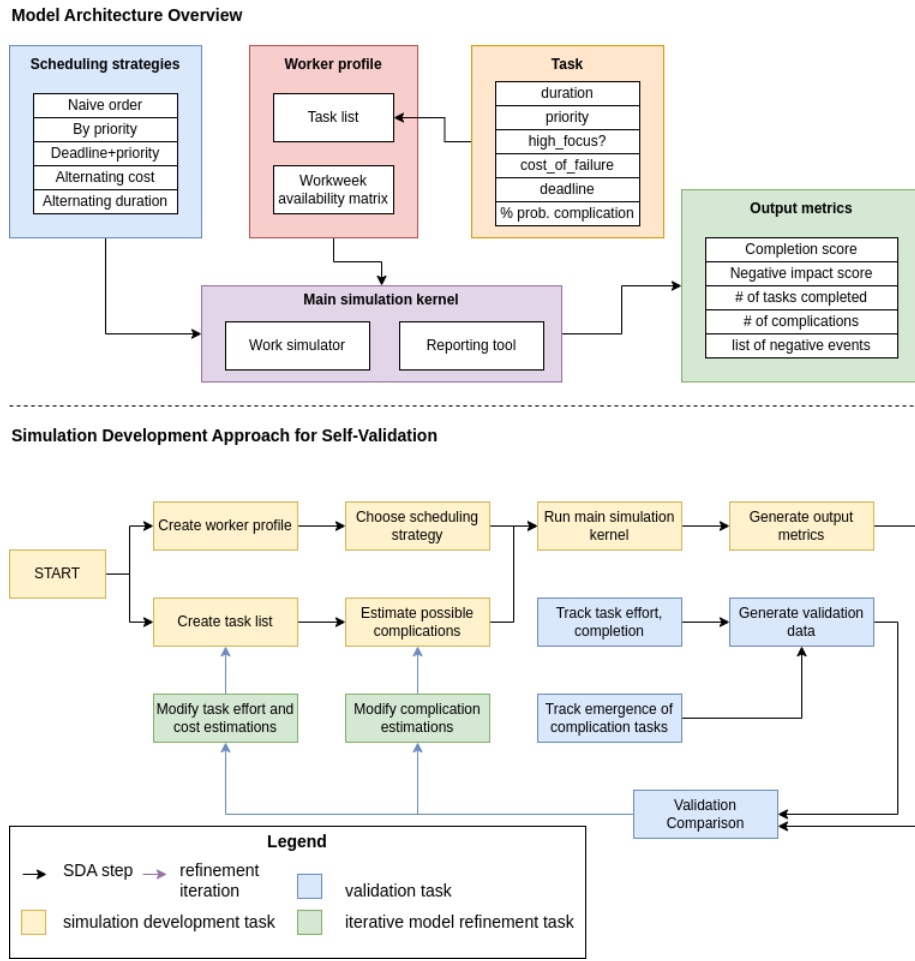


Fig. 1. Top: architecture overview of R2. Bottom: SDA overview of a self-validation with R2.

Tasks vary widely, from quick note-taking to intensive coursework, with a task cost mostly between 1-3, though crucial submissions may escalate to 4 or even 5, risking course failure.

In addition, we have implemented five basic task scheduling strategies to investigate to what extent these can affect the work outcomes for each of the three workers. These strategies are:

- **naive**: processes tasks in the order they are put in, without considering priorities, deadlines, or other attributes. This approach serves as a baseline.
- **priority**: prioritises tasks based on their priority value, with higher numerical values indicating higher priority. This strategy ensures that the most critical tasks are addressed first.
- **deadline+priority**: prioritises tasks based on their deadlines, addressing the most urgent tasks first. If tasks have the same deadline, it then prioritises them based on their priority.
- **alternating_cost**: balances the workload by alternating between tasks with the highest and lowest costs, where cost reflects the cost of failure. This approach aims to maintain a steady work pace and prevent burnout by alternating simpler tasks with more complex ones.
- **alternating_duration**: similar to the Alternating Cost Scheduler but focuses on task duration. By alternating between the longest and shortest tasks, it aims to create a balanced schedule that avoids prolonged periods of intense work, making the workload more manageable.

To showcase the behavior of our simulation code, we have performed 1,000 simulations for each combination of the three worker types with the five scheduling strategies. All our simulations were performed on a local desktop, and required approximately ten seconds to complete.

We present the results from our exemplar workweek simulation runs in Figure 2. In this figure, the error bars span from minimum to maximum score levels, accounting for the uncertainty of complication tasks arising. When it comes to completion score, we find that the uncertainty caused by the possible emergence of complications is larger than the difference between scheduling strategies. As a result, the effect of choosing different task scheduling strategies is not “statistically significant”, which in this case means that possible complications can lead to situations where the best initial choice of strategy does not necessarily lead to the highest completion score. We observe a similar pattern in the effort multiplied completion score, but for the negative impact score the differences are more pronounced, particularly in the case of the student who faces relatively tight deadlines. When we look at the effort multiplied task completion score, we notice large differences between the manager, the software developer and the student. This metric is greatly affected by the task list provided, and the relatively long tasks of the software developer lead to higher scores in this regard (the distribution of priority values is similar across the three exemplars).

In terms of negative impact, all three of our workers were given a very demanding task lists to demonstrate the behavior of the code. Given that missing

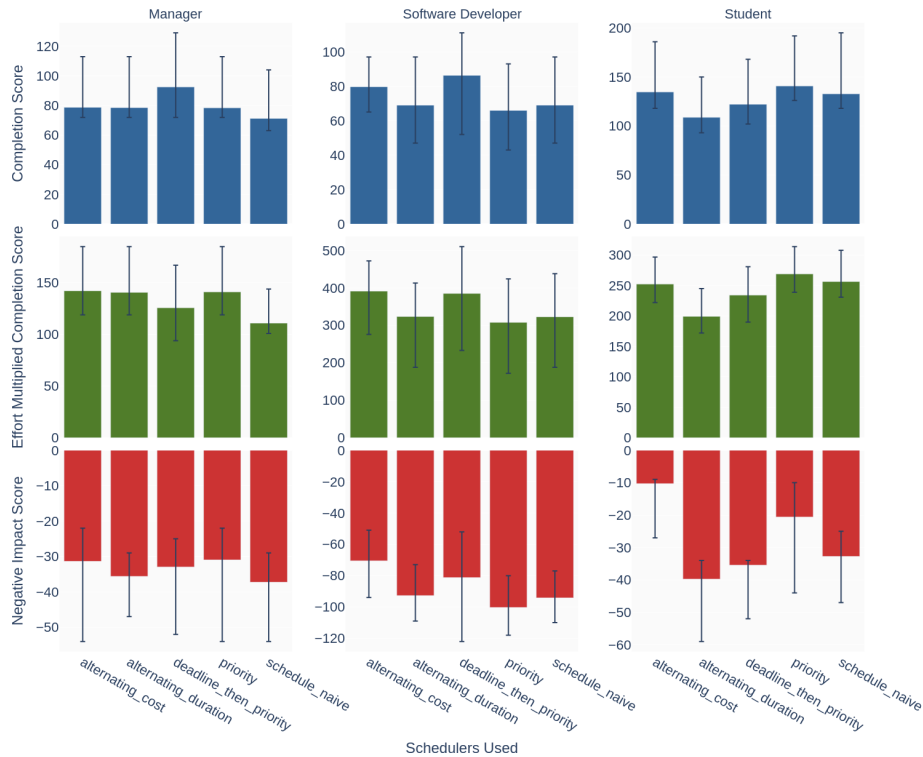


Fig. 2. Metrics Comparison Across Schedulers and Personas. Results of workweek simulations for the three exemplar workers: manager (left), software developer (middle) and student (right). Note: error bars indicate the full expected range of performance possible by the worker (maximum and minimum), accounting for the uncertainty of complication tasks arising.

out on a task with a cost of 5 (desperate) increases the negative impact score by 25, we can observe that the workers reach a negative impact exceeding that level in almost all cases. A notable exception is the student that adopts the alternating cost strategy, as in this case the negative impact remains remarkably limited. Overall, the results showcase that R2 is clearly sensitive to: (i) differences in task and effort properties of the three archetypes, (ii) different task scheduling strategies and (iii) probabilities of complication tasks during the week. As a result, we argue that our model can be adopted meaningfully by individual users for further experimentation and validation, following the SDA presented in Figure 1. To further investigate the effect of complications on the results, we performed runs with differing complication probabilities, including runs with 0% and 100% probability. Here we find that complications increase negative scores by approximately 50 to 150% (manager), 20 to 150% (software developer) and -30% to 400% (student), depending on the scheduling strategy chosen. Here, the two alternating strategies in particular can lead to dramatic and counter-intuitive changes in the negative scores. For space reasons we provide our full result plots at: https://github.com/djgroen/r2_iccs2024_public.

4 Discussion

Within this paper we presented a new approach to simulation development, intended to be adopted by individual workers to better understand the dynamics of their working week. We showcased our prototype implementation by applying five different task scheduling strategies to three archetypal worker situations, and demonstrated that the simulation results are sensitive to factors such as the presence of complications, the nature of a worker’s task list and availability, and the choice of task scheduling strategy.

Our code is intended for use in private by workers themselves. It is therefore essential to make the tool particularly easy-to-use and easy to deploy (hence the choice for a web service). The private setting of use for the tool does give rise to validation challenges. Although a large-scale evaluation test with data collection can be done, the way we defined the SDA (see Figure 1 puts the workers themselves in charge of performing the validation. When doing such a validation, workers will use R2 for a working week and then compare between the initial tool forecast and their perceived reality. This includes comparing the predicted tasks completed vs. the actual ones (given the task allocation strategy they used) and comparing the perceived negative events incurred vs. the ones predicted by R2. Based on the validation outcome, the user can adjust assumptions in the simulation, for instance by modifying the duration or consequences of specific task types, modifying the effort schedule, or modifying the probability and impact of task complications. At time of writing, we are not aware of any other simulation development approaches that explicitly incorporate self-validation by the end user. We therefore encourage the community (including ourselves) to explore to which extent self-validation could be applied in other domains of simulation development.

This self-validation does have limitations: for instance the validation performance by one user does not necessarily hold for other users because the modelling approach relies so heavily on self-defined assumptions. In addition, the quality of the validation procedure depends on aspects such as intrinsic bias in the worker’s mindset and the quality of the simulation user interface. However, the choice of workers as target users greatly expands the potential user base of the tool, and the possible positive impact it could have on society. Our ambition is that, by introducing this working week simulation and self-validation tool, we can help workers to learn about the task and effort dynamics in their working week, and their overall mental experience of it.

Lastly, there are many avenues that we have not yet explored. For future work, we’d like to (i) incorporate mechanisms where negative events incurred during the week could affect worked productivity in the remaining period, (ii) develop a user-friendly approach to define complications, (iii) explore how ad-hoc meetings or pre-emptive strategies of workload mitigation (e.g. requesting deadline extensions or scheduling overtime) affects completion scores and negative impact scores, and (iv) identify typical working weeks in different professions, in terms of the tasks given, their priority, cost and possible complications. Aspects

(ii) and (iv) are directly relevant for the user, as both enhancements make it considerably easier for them to use the simulation platform.

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