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Doctoral Thesis

Development of human-centric assembly systems using Virtual Reality

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2023

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Development of human-centric assembly systems using Virtual Reality

A thesis/dissertation submitted to
Ulsan National Institute of Science and Technology
in partial fulfillment of the
requirements for the degree of
Doctor of Philosophy
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Development of human-centric assembly systems using Virtual Reality

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Abstract

Despite recent advances in disruptive technologies like automation, machine learning, artificial intelligence, and virtual reality, humans remain a precious resource for manufacturing assembly. Paradigms such as Industry 4.0, IoT, digital twin, and cyber-physical systems emphasize the convergence of connectivity, integration, high-fidelity simulation, and heterarchical systems architectures to develop complex integrated systems. More recently, Industry 5.0 places the human operator at the center of system design, but due to human-machine interfaces, developing such systems is challenging. The introductory chapters describe the changing role of the operator in manufacturing and motivate the development of human-centric solutions.

This thesis investigates the development of human-centric systems by leveraging virtual reality for digital workstation prototyping. To this end, the first core chapter reports a study confirming that a virtual workstation can measure data crucial to manufacturing assembly, specifically, the throughput rate, risk of defective assemblies, and assembly errors. This study aims to increase confidence in data acquired from the simulation and serves to convince skeptics.

After confirming that we can acquire meaningful data, the second study applies this technique to a decision framework for suggesting the best manufacturing design. This illustrates the usefulness of this technique in digital prototyping and product design. The results also illustrate that this technique can be used to plan workstation and factory layouts to meet production requirements.

The prior two studies revealed that human trials are costly and time-inefficient, as experiment designers often acquire ample data. The third study addresses this issue by developing a data-efficient experimental framework. This framework uses an active machine learning model that adapts the design experiments online. This illustrates that VR simulation can include an intelligent system and move from a passive framework for acquiring data to an intelligent one with adaptive control.

A deeper inspection revealed that the active model can be used for sample-efficient modeling and control simultaneously. This presents an ethical issue as controlling human systems removes the operator's free will. The next two chapters investigate a method of controlling human systems based on extracting the human internal state. Such a system would optimize for production but also for the operator's health.

To investigate using the active model for control, a fourth study applies this technique to the control of non-human systems, showing it can be extended with application-specific constraints.

In conclusion, the framework for developing human assembly systems using virtual reality reduces capital and technical investment risk. Confirmation of measurement via simulation, application of data acquisition, and data-based control applications appear as logical steps. Control of human systems presents some ethical challenges, and we suggest a theoretical approach.

The methods described herein will facilitate the development of modern human manufacturing systems by providing a framework that can be applied to the development of new systems and the retrofitting of existing ones. This work is also valid for other physical fields like medicine, mining, and engineering.

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Technical terms and abbreviations

Term	Definition
System	An entity composed of several interacting components. Each component can be subsystem, making the estimation of the state challenging.
Complexity	The impact of change of state through interacting components. For example a system with multiple interacting components is complex, where a system with interacting components is complex.
HITL	Human in the loop. Methods that use an actual human as appose to simulating the human response.
DAL	Deep active learning
AD	Axiomatic Design
DfAM	Design for Additive Manufacturing

1. Introduction

This chapter presents an introduction and background of human operators in manufacturing. It motivates the use of an immersive human-in-the-loop approach motivated by recent economic and technological advancements.

The subsequent sections of this chapter will delve into the following aspects:

1.1 Background

1.1.1 The role of human's in manufacturing

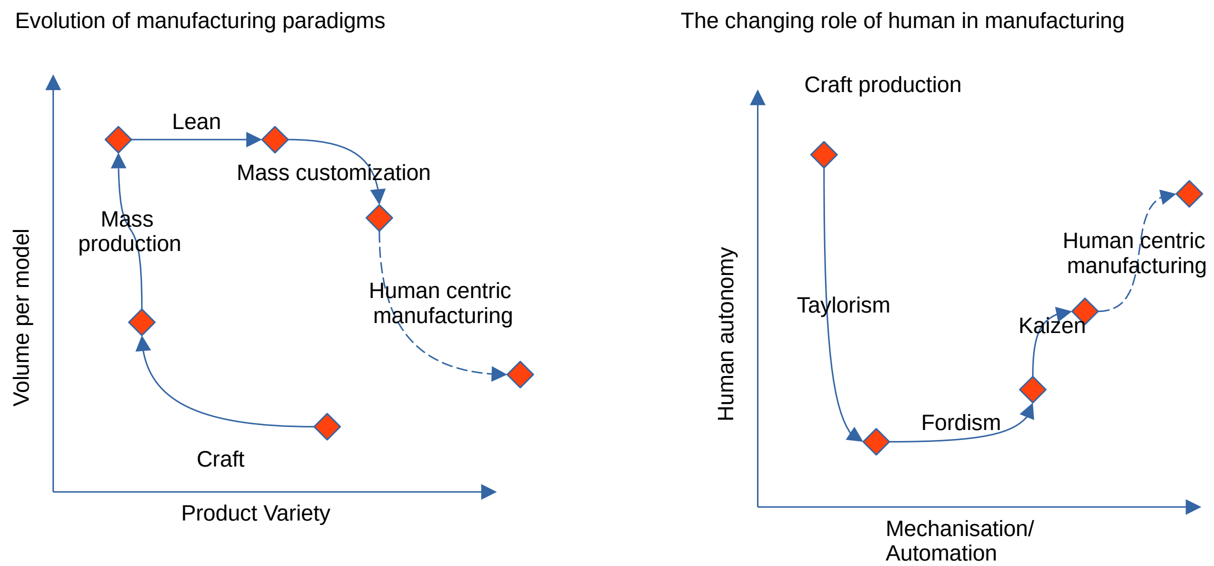
Manufacturing systems has experienced several paradigm shifts to remain progressive. Humans remain a crucial element in manufacturing but their role has changed through.

Koren offers a the largely accepted evolution in manufacturing paradigm [1], but does not place the human operator in context. We address this by concurrently reflect on the role of human operators on a similar timeline.

Before the 1950's, craft production had human operators express their creativity with single-lot-size made to customer specifications. This was characterized by large product variety and small volume batches. Here little mechanization was available due to wind, water, and steam power. The industrial revolutions brought seemingly unending source of constant energy that, combine to advances in mechanization, lead to significant increases in productivity. This mass production age, was characterized by high volume batches and small product variety. The lean manufacturing paradigm, sometimes called the Toyota way was characterized by just-in-time manufacturing, where costs were lowered by only manufacturing what was needed, reducing surplus and overall cost [2]. These also allowed a more product variants since each product was customized to order.

Mass customization is the pursuit of smaller batches of products that solve customers specific needs. The paradigm is characterized by large product variety and significantly lower volume batches. Earlier works in this area seem to ignore the human operator. Flexible manufacturing systems require high capitol investment and have low volume output [3], reconfigurable manufacturing systems that attempt to stagger the capitol investment with production volume [4], [5], and holonic manufacturing systems mimicking natures self organizing patterns [6]–[9]. While these shifts have provided nominal increases in productivity, the increased complexity and regular modification due to product variety is an active research topic.

This direction has led to one critical oversight, "humans are a naturally flexible and adaptive resource". Recently, Elon Musk famously tried over-automate when producing the Model 3 [10], claiming "excessive automation was a mistake" and "humans are underrated" [11]. [12] highlights that high levels of automation can result in products that are challenging to assemble, increasing overall cost.



From a different point of view, craft production utilized human creativity and was characterized by high-levels of human-autonomy and low-levels of automation. The age of Taylorism greatly increased efficiency by reducing operations to simple repeatable tasks [13], [14]. This models humans as machine resources, with low levels of autonomy and is associated with worker dissatisfaction. Many practices would be considered unethical by today's standards. Fordism took a broader look, improving production instead of individual tasks, leading to greater employee autonomy and satisfaction by utilizing mechanization like the moving assembly line [15]. Both Taylorism and Fordism enabled mass production.

Lean manufacturing, although enhancing productivity, necessitated continual refinement of products and manufacturing systems. This evolution brought about the concept of Kaizen, or continuous improvement. It remains uncertain whether (1) managers soon recognized that operators could more effectively enhance manufacturing processes through their firsthand experience or (2) the increased autonomy of workers resulted in greater job satisfaction and reduced human errors. Nonetheless, Kaizen bestowed upon human operators a heightened level of autonomy, marking a significant departure from micromanagement.

Since then the adaptability of human operators have been recognized and efforts have largely focused on enhancing human performance through robot collaboration and digital assistance in the form of operator 4.0 [16]–[18].

On the other hand, enhanced mechanization has been associated with a number of high-profile accidents due to exhaustion, cognitive load, stress, and loneliness [19], [20]. This issue has been observed in as medical misdiagnosis, manufacturing injury, and boat crashed of seafarers [19], [21], [22]. This is indicative of the wicked/complex nature of socio-technical systems, namely "changing elements may change the systems/operators behavior" [23]. Blindly relying on technology cannot resolve human issues. Just as high-profile accidents result from a failure to account for the cognitive burden imposed by technology, a parallel trend persists in research where the cost of data acquisition goes unacknowledged.

1.1.2 Human-centric manufacturing systems

Human-centric manufacturing places the human at the core as an essential resource. This recent and high-level statement has conflicting interpretations. For example, there is a need for cognitive, sensorial, and physical support [24], while framework's encourage numerous wearable sensors [25] and presents operators with rich information [26]. Another perspective is the move from a techno-centric to a human-centric approach [27]. This frames the task as applying existing technology in a human-centric way, for example moving from 2D simulation to virtual reality. While this interpretation is more actionable, without the human operators feedback it stands the chance of reverting to its techno-centric root. Due to the complex nature of socio-technical systems it becomes clear that rapid and incremental prototyping is required.

Another prevalent method is simulating the human operator. While this may be practical in future, a few limitations currently inhibit its application. Firstly, issue is that human models are typically only valid in a small domain, due to task complexity [Moise]. This means models must be validated and tuned using actual human data. Secondly, complex models will be required to capture performance and operator satisfaction states. This increases the data requirement from the operator.

1.1.3 Measuring human operators and HITL simulation

Owing to modeling being so challenging much of the recent effort has focused on measuring the human operator. While much of this work has been done in a medical setting, only 3 works considered blue collar workers found a recent review [28]. The review also finds medical, physiological, and vision based sensors to be impractical for manufacturing applications. Few works consider the impact of wearable on performance, but some work illustrates that discomfort caused by devices can increase human-error rates [29], suggesting a correlation between operator discomfort and negative-performance. The unchallenged assumption of Operator 4.0 that measuring and human-machine interaction is without cost is slowly being realized. Additionally, numerous previous works have established a connection between operator performance and human internal-states like fatigue and learning/skill [22], [30], [31], suggesting that human states can be interfered without additional sensors. For these reason's a practical approach may be human-in-the-loop (HITL) iterative development of socio-technical systems.

The HITL approach allows for complex simulation is not without cost. Human operator trials are significantly more expensive than computer simulations or lower fidelity trials. The design science methodology suggests that we acquire knowledge from implementing systems. For example, it became evident that an adaptive design of experiments (DoE) approach could reduce the number of operator trials (chapter 3).

1.1.4 The human need in manufacturing systems

There is a growning body of research investigating human-centric manufacturing paradigms. For example, [32] highlighted investigated key factors affection adoption of CPS found (1) humans CPS includsion is difficult, high-priority, and high adoption effect. A review of flagship reconfigurable projects in Europe found that only 3 out of 15 projects considered human integration [33]. mentioning that humans are a flexibility driver HITL and HMI should be prioritized.[34] mentions human interoperability with software and hardware as a challenge. [35] suggests (1) lack of appropriate abstraction (or reference architectures), (2) complex requirements, and (3) design, implementation, and maintenance patterns as a challenges. [27] suggests the human digital twin is a key issue for the successful CPS. [36]

1.2 Motivation

The complex and dynamic nature of modeling human behavior necessitates continuous validation. This underscores the importance of employing Hardware-in-the-Loop (HITL) in the prototyping and development of human systems. As the trend towards a human-centered approach gains momentum, there is a shift away from treating humans as mere machines. Instead, we are now integrating human factors and ergonomics into our systems. Given the intricate nature of human behavior, coupled with the ever-evolving landscape of manufacturing technology, the pursuit of modeling human-centered socio-technical systems is a constantly moving target. Case studies play a pivotal role in unearthing novel insights and knowledge in this domain. While techno-centric approaches remain viable, it is increasingly likely that a human-centric approach involving rapid and incremental iterations through HITL simulation will be instrumental.

1.3 Objectives

The objective of this research is as follows.

1. Development approach to human-centered solutions that encourages constant iteration.
2. A HITL framework to quantify the human performance for manufacturing assembly.

1.3.1 Development approach to human-centered systems

Given the unpredictable nature of modeling human behavior, a development approach that encourages constant iteration is essential. This approach views a system as constantly evolving, facilitating continuous iteration, data generation for model validation and tuning, and reducing the risk of detrimental changes.

1.3.2 A framework to quantify human performance

The research aims to develop a framework for quantifying human performance in manufacturing assembly, addressing the complexity of human performance metrics, their interactions, and their impact.

1.3.3 Measuring Human Operators and HITL Simulation

Owing to the challenging nature of modeling human behavior, the research focuses on measuring the human operator. It is acknowledged that this work is primarily derived from medical settings, and it emphasizes the need for practical human-in-the-loop (HITL) iterative development of socio-technical systems.

The HITL approach is acknowledged to be costlier but provides valuable insights. The research is aligned with a design science methodology that seeks to acquire knowledge through system implementation.

1.4 Problem statement

1.4.1 Assumptions and research scope

We constrain our investigation to manual manufacturing assembly tasks, providing informatics and feedback through simulated displays and audio feedback, explicitly blocking ergonomically challenging, dangerous, or physically exhausting tasks.

1.4.2 Hypothesis

Two hypotheses are formulated in line with the research objectives:

Hypothesis 1: Virtual reality can effectively and feasibly be employed for digital prototyping of manual assembly tasks. This hypothesis is explored through questions related to data validity and contributions to existing models.

Hypothesis 2: We postulate that this digital prototyping tool has the potential to serve as a catalyst for the creation of innovative applications that can subsequently be implemented in physical prototypes. The research aims to explore and validate this process through simulation case studies.

1.5 Research strategy

The results of this research loosely follows the design science research methodology of "discovery by implementation" [37]. Practical case-studies were initially implemented, leading to novel insights. For example, chapter 4 uses HITL-VR to simulate the assembly of several additive manufacturing designs. It became evident that the cost of human operators in HITL simulation was significant, therefore chapter 3 developed a sample efficient method reducing the number of experimental trials. Chapter 2 then generalized results by demonstrating that multiple performance metrics can be extracted from the same simulation (task duration, human-error risk, and assembly error). Hereafter, we can (more confidently) make statements about our the development process we suggest in chapter 5.

The following methods were used:

1. Literature reviews assessed the state of the art and formed requirements for current and future assembly systems.
2. Simulations were developed for each case study, constructing the virtual workstations, conducting simulations that produced data, and validating the results.
3. The research is conducted across chapters that progressively build on each other to generalize findings and make actionable statements about the proposed development process.

1.6 Dissertation overview

This dissertation is presented in a multiple manuscript format, with chapters 2, 3, and 4 appearing as individual research papers.

The overview of the dissertation is as follows:

1. Chapter 1 provides background, motivation, objectives, problem statement, and research strategy.
2. Chapter 2 proposes HITL virtual reality as a means of complex simulation and validates its applicability through specific tasks. This chapter generalizes and given validity to this research.
3. Chapter 3 addresses scalability issues using HITL-VR simulation by introducing an adaptive sample-efficient scheduling technique that the number of human trials required and allows concurrent, remote, sample-efficient simulations by addressing limitations in previous work.
4. Chapter 4 demonstrates the use of assembly simulation to rank additive manufacturing designs. Illustrating the frameworks application to a modern problem.
5. Chapter 5 presents the design pattern used to develop these systems.

6. Chapter 6 concludes the research by summarizing the impact and contributions of the work.

2. Complex human performance data acquisition from virtual manufacturing assembly simulations

2.1 Abstract

The recent announcement of industry 5.0 is an effort to move from techno-centric to Human-centric manufacturing, yet measuring human operators' performance presents significant practical challenges. To address these concerns, we explore the potential of virtual reality (VR) assembly simulations as an efficient tool for acquiring operator data with the objective of addressing practitioners skepticism by bolstering confidence in its suitability.

The objective of this work is to enhance confidence in the suitability of VR simulations for manual assembly tasks. To achieve this we conduct simulations of four common assembly tasks, validating task duration, quality-risk/risk-of-defect, and assembly error. We (1) compare the task duration and quality risk against established models Wright-learning and Risk-index, (2) propose assembly displacement error graphs to quantify assembly error dimensions, and (3) expand Wright-learning from a deterministic to a probabilistic model.

Our findings demonstrate that VR simulations (1) closely resemble well-established models, affirming their utility in modeling human behavior from assembly time and quality risk, (2) can measure data that is not practical in the real world such as assembly errors in manual assembly processes, and (3) can be used to explore novel areas, such as extending existing deterministic models to probabilistic ones.

While our study encourages the use of VR simulations in human performance modeling, further investigation is essential to validate alignment with real-world performance. Practically, the relative performance results obtained through VR simulations hold promise for designing, improving, and comparing operator assembly tasks, workstations, and configurations.

2.2 Introduction

Humans continue to play a crucial role in manufacturing assembly, despite advancements in automation. The concept of human-centric manufacturing has emerged as a strategically significant topic for Industry 5.0, as emphasized in a recent EU report [38]. In fact, manual assembly remains prevalent in six out of the eight target markets outlined in the Made in China 2025 initiative [39]. Yet, ever increasing wages and cognitive load due to modern equipment require that we optimize the precious human resource. These evolving circumstances highlight the growing significance of human operators and the increased responsibility placed on ergonomists in recent times.

A recent special issue investigating new human factors methods mentions “the changing nature of work and increasing use of technologies such as artificial intelligence and big data are raising questions about the utility of HFE methods” [40]. These transformative technologies demand novel approaches to experimentation and an expanded scope of data acquisition.

One disruptive technology is modern head mounted virtual reality headsets. These (1) offer an immersive experience, (2) are becoming easier to develop through free game engines, and (3) are decreasing in cost. All while reducing the burden of conducting experimental trials by automating data-acquisition, easing reconfiguration through a software environment, providing scalable and high fidelity data. VR simulations are quickly becoming financially and practically viable for human experiments. Yet when interviewed, human factor researchers raised concerns about the reliability of this technology [41].

The general objective of this work is to increase practitioners confidence in VR by validating its ability to simulate operators performance in manufacturing assembly tasks. We do this by:

1. Confirming the measured throughput rate and assembly quality conform to well known models . This illustrates that VR simulations can observe the human state.
2. Measuring the assembly error, which would be difficult to measure physically. This demonstrates VR simulations are able to measure things that are difficult to measure in the physical world.
3. Enriching the wright learning model from a deterministic to probabilistic one. This demonstrates that VR simulations can explore novel areas.

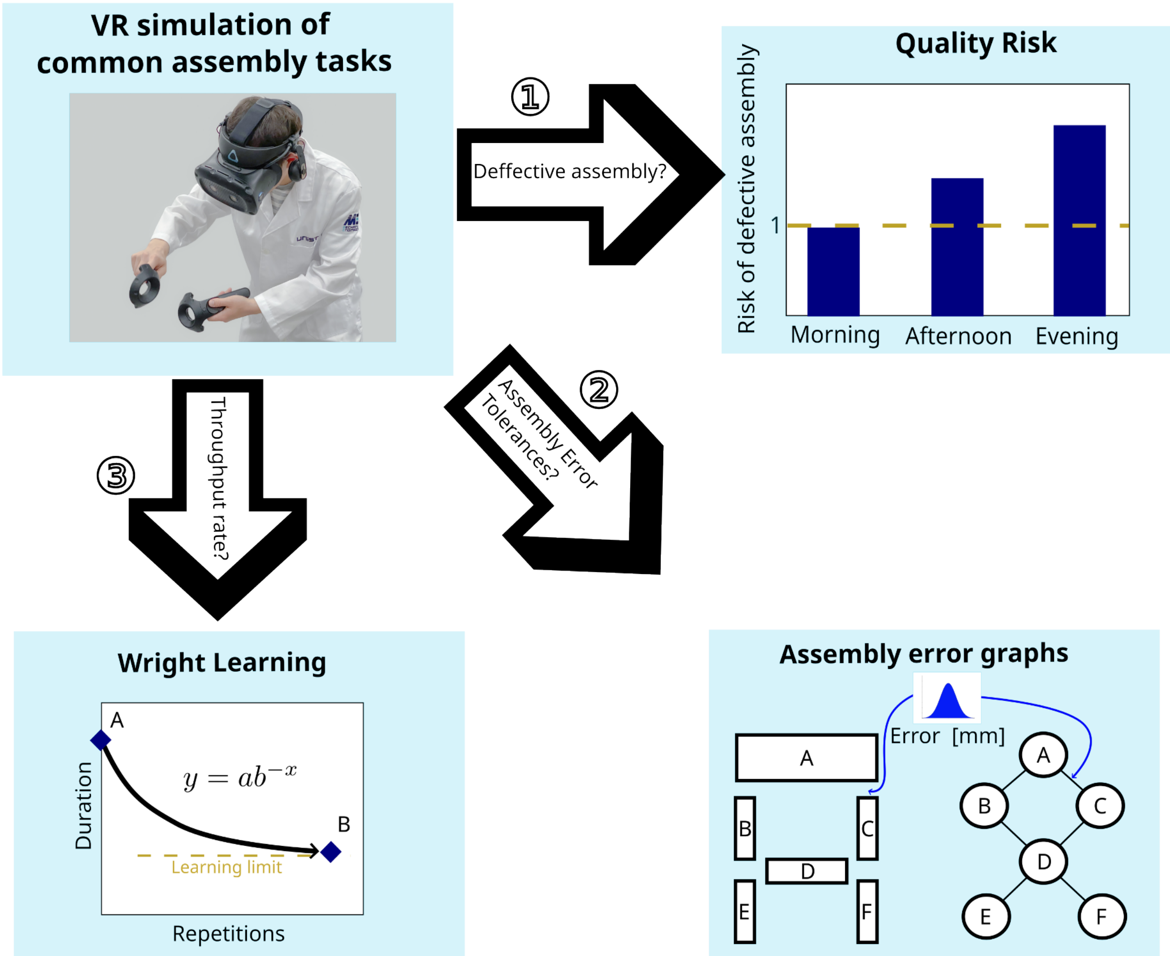


Figure 1: The research methodology overview

Figure 1 illustrate the investigations overview. The remainder of this article is organized as follows. The literature review (1) provides a concise overview on human assembly in manufacturing and VR and (2) discusses the established human performance models and how they were adapted. Section 3 states the research question. Section 4 describes the design and development of the simulation. Section 5 discusses the experimental design and data collection from the study. The verification/validation is described in section 6. Section 7 concludes the study.

2.3 Literature review

2.3.1 Industry 5.0

The industry 5.0 movement is value driven described by human-centric, sustainable, and resilience [42]. These three values interact in a complex manner and are expected to result in socially and economically responsible advantages. The requirements of human-centric manufacturing systems are not entirely clear at this point. Futuristic perspectives describe human-robot collaboration, driven by AI using voice command and human-intent through real-time data acquisition [43].

One productive interpretation is “the shift from a techno-centric to a human-centric perspective” [44]. This frames the current task as applying the I4 techniques (IoT, Digital twin, AI, CPS, Cloud-computing, etc.) in manner that is accessible and beneficial to humans. For example, in industrial robotics and autonomous driving applications, simulated environments are used to virtually prototype solutions and train machine learning models [45], [46][ROS, Kuka-simpro. ABB robotics sim]. Similarly, VR offers similar opportunities for human-in-the-loop simulation, provided the simulated data resembles that of the real-world.

There is a growing interest in including human factors and ergonomics (HFE) into manufacturing systems applications [47]–[53], but complexity fractures these efforts. For example, [54] suggests that when HFE is exclusively viewed through the lens of social and ethical concerns, without being linked to financial and profitability considerations, it risks becoming disconnected from management research and decision-making processes. Where [34] suggested a control loop for general cyber-physical systems between operations research, data-science, and control. [54] applies this loop to HFE alluding to ethical control of human systems with hidden state variables like well-being. These examples illustrate this is a complex problem and will likely require creative and multi-disciplinary approaches.

2.3.2 VR for complex HITL simulations

VR has been successfully applied to a number of application. In safety training is used to dangerous environments [55] and has higher motivation and knowledge retention rates [56]. Another popular application is visualization and design review [57]. A recent review found that workspace design (15%) and assembly training (19%) were the second most researched areas, with assembly guidance (47%) leading, likely due to augmented reality integration[58]. Here we are more concerned with acquiring data from the human subjects.

To this end a few VR experimental frameworks have been developed. [59] proposed an experimental design framework with the ability to conduct remote experiments by sending acquired-data to a remote database. [60] took it one step further by using an active machine learning model to design experimental conditions on the fly, with the goal of reducing the number of experimental trials. [61] created a decision framework that integrates VR human assembly data and 3D printing data to suggest the best alternative among consolidation designs.

Previous training modules for manufacturing assembly have validated a reduction in perceived workload [62] and fewer assembly errors [63]. The objective of this work is to demonstrate VR as complex simulation with the ability to simultaneously simulate several human performance behaviors.

Simulation complexity is a characteristic of I5.0, particularly relevant to the Digital twins. This is the ability to consider a wide range of outcomes. Typically simulations reduce complexity by isolating interacting parts/sub-systems limiting the range of outcomes and computation complexity. A complex simulation would simultaneously predict the outcome for several phenomena and the interaction between them, while several simplified simulation would be needed and would not account for interaction. The simulation in this study simultaneously predicts throughput rate, risk of defect, and assembly error. These simulation predict (more holistically) the effects of design changes and lead to insights about the human state [64], [65], making them better suited for a value driven approach.

Complex simulation is typically more difficult to develop and more computationally intensive because of the interaction between phenomena. These effects are mitigated by using Human-in-the-loop (HITL) simulation. HITL simulations are more costly than computational simulation due to the human labor required. This issue was addressed by using DoE methods to reduce the number of trails [60]. This poses that HITL and computational simulations are not exclusive but should be used in conjunction.

2.3.3 Human performance models for dynamic scheduling

Operators are a critical resource for most assembly systems. Properly scheduling personnel to consider human capabilities can optimize system performance, increase personnel well being, and increase task learning [66]. Scheduling belongs to a family of NP-hard problems, which are not always tractable and therefore [67] suggests that machine learning techniques will become increasingly important. Advances in deep learning automatically modeling human internal state seems promising [64], [65], but these require data accurate data for training. Here, VR simulations can play a key role by providing relevant data.

This section describes the relevant models being considered here. Specifically, Wright learning to predict throughput rate, Risk index to predict quality, and assembly graphs for assembly error.

2.3.4 Wright learning in manufacturing assembly

Wright's curve predicts the cumulative gain in productivity through scale. It was first used to predict the cost of airplane parts [30], but has since been used to predict the cost reduction in microchips [68], lithium ion batteries [69] and is a well known economic tool.

Wrights learning curve models the throughput rate of manual assembly tasks by predicting the task duration based on the number of previous repetitions. These laws typically follow a decaying power law, see figure 1 C, with a learning-limit or incompressible work asymptote [70]. This allows predicting the throughput rate of human process performance over time and is particularly useful in flexible manufacturing environments, with regular product/production changes.

Wright learning has been proposed for dynamic scheduling and has received numerous extensions including factors like circadian rhythm rest, task complexity [71], prior-experience [72] fatigue [70], [73], learning-forgetting, and rest-pause [74]. [75] provides a review of some models.

All previous models the authors have come across are deterministic. It is not clear whether this is due to the effort of acquiring high-frequency data as opposed to taking averages. To our knowledge this is the first work to propose a probabilistic learning curve. This is made practical by per task duration instead of batch averages, which is achieved with VR automating data acquisition.

Modeling learning in VR is attractive for two reasons. Firstly, because it quantifies throughput rate and can be used to plan manufacturing system layout, load balancing, and dynamic scheduling. More generally, it quantifies the benefits from VR training. Combining these would result in a pre-training tool that simultaneously predicts the throughput rate and trains the individual on the task at hand. Wright learning is a good model for validation due to its simplicity, usefulness, and maturity.

2.3.5 Human fatigue and quality risk

Human fatigue in human performance models can be thought of as “the reduction in performance due to prolonged exposure”, affecting cognitive and physical performance. Human fatigue has been responsible for injury and defective assembly in mining and engineering applications. Therefore scheduling to reduce risk is beneficial. Modeling fatigue has proved difficult, despite several attempts. This appears to be due to varying definitions. Since fatigue is a hidden state that can not be measured directly, only its effects are measured and the state must be inferred. For example common effects of fatigue are lower alertness, slower response time [76]–[78], increased task duration [31], reduced learning [73], and reduced physical performance [21].

The flexibility of the operator has significant impact on the measuring technique. Fatigue estimation/measurement is more mature in applications were operators work in structured environments. For example long-distance drivers and pilots operate in structured cockpits and have seen a large body of work [79]–[85]. These include sensors in steering wheels, chairs, and eye-monitoring cameras [80], [82], [83], [86], with some products reaching commercial viability.

On the other hand laborers work in unstructured environments like seafarers have been intensively researched after a number of high-profile accidents correlate with late night and unfavorable working conditions [87] but have are impacted by the additional constraints. For example, physiological measurements such as EEG, ECG, temperature, position, etc. appear to be common [88], [89], but outfit the operator with signal sensors that are invasive and inhibit operator performance. Biological samples like oral swabs [19] are equally impractical due to intrusive, time consuming, and cost prohibitive nature, but are suitable for validating models. For these reasons, works like [88], [90] investigating effects and causal factors of fatigue are important. In this work, we found VR can play a role in providing insights on how to estimate fatigue through production data which is suitable for a flexible virtual environment.

Manufacturing quality has been a crucial metric in manufacturing for decades as it is associated with waste-reduction, cost reduction, and reliability/consumer-image of the product. In production “quality refers to the extent to which the product assembly process is executed without deviations from the required process resulting in a defect-free product”. Processes are often scrutinized for quality improvement potential.

One specific measurement that is drawing increased attention is the fatigue quality relationship. [47] reviews the relationship between quality and human factors, mentioning that human factors was previously only concerned with safety and quality performance should be considered. This prompted a follow up [48] quantifying the effect as variance. [91] presents a systems dynamics model of quality risk.

The quality fatigue relationship is inherently difficult to model, due to the low number of defective parts skewing data. Literature hints at an exponential decay in human performance, for example [21] states that medical interns who worked traditional shifts of 24 hours or more where five times more likely to make serious diagnostic errors than those whose shifts lasting only approximately 16 hours. Attempts at modeling fatigue also exist [77] but have not been extensively used in literature. Finally, human error probability (HEP) models quantify the likelihood of a human error, considering the task complexity, operator experience, and fatigue etc. These are used in manufacturing, medical, and nuclear applications and are typically expressed as a percentage.

A seminal study [20] provides the Risk-index model with strong evidence that increased fatigue results in increased chance of injury. See figure 1 A. The study specifically shows relative injury risk increases (1) later in the day and (2) after subsequent workdays. Here time of day, previous workload, time-since last rest, and number of consecutive shifts were the factors of interest.

This work makes two adaptions to the risk-index model. Firstly, the original study proposed the Risk-index to assess risk of injury. Instead, we adapt this concept to quality risk to assess the **risk of a defective assembly**. The reasoning is that fatigue related cognitive performance degradation is the likely cause of injury, and would similarly result in defective assemblies through errors in judgment. Secondly, the relative risk index in order to assimilate data from different industries into a single model. This scales the risk by dividing all periods by the morning risk. These simulations do not have the same issue. Instead we use **defect ratio** to quantify risk. This is the ratio of defective assemblies to total assemblies. This has the advantage of preserving the ratio that it can be compared across tasks, unlike risk-index and complies with current HEP conventions.

2.3.6 Assembly error graphs

Assembly dimensional error quantifies the variation in the dimensions of assembled components. It is a continuous value as appose to the discrete defect (or not-defect) metric of quality risk.

Assembly graphs serve as an intuitive means to depict the assembly process. In this representation, each component is visualized as a node, while their connections are depicted as edges. Sub-assemblies can be conveniently portrayed as sub-graphs that encompass the respective sub-assembly's components.

These assembly graphs have proven invaluable, particularly in the realm of assembly sequence planning, as extensively discussed in [92], [93]. In these contexts, CAD files are meticulously examined to uncover multiple assembly sequences. However, due to the intricate computational nature of this task, researchers are actively exploring ways to infuse data-driven insights and human expertise into the decision-making process, as highlighted by ongoing efforts in [94], [95].

Our research takes a distinctive approach by modeling assembly errors akin to tolerance specifications. In this paradigm, each edge in the assembly graph signifies the error in component placement across six degrees of freedom (6-DOF). This graph-based representation provides us access to a well-established arsenal of mathematical tools and facilitates effective visualizations. Also it structures the error data, allowing one to recommend specific components/interface contributing to tolerances. It is noteworthy that this area of study remains relatively under-explored. Prior work, such as [96], has employed stochastic simulations to estimate tolerances, whereas our approach leverages data from virtually assembled components. Collecting such data in the physical world is often impractical, underscoring the novelty of our methodology. Furthermore, our utilization of Virtual Reality (VR) for measuring assembly error enables us to quantify both assembly cost and error proactively through virtual prototyping. The inherent structure of the graph may offer a deeper and more nuanced understanding of the contribution of each component to the overall error, a level of insight that is often challenging to attain in the physical world.

2.4 Research questions

This study aims to increase practitioners confidence and interest in VR simulations. Firstly, the confidence is increased by validating its ability to observe human state during manufacturing assembly tasks. Put more simply, "Do the results from a VR simulation resemble well known models of human performance?" Secondly, we explore whether VR simulations can be used exploratory to discover new insights from the data provided. This illustrates VR sims can be used for novel discoveries and are not limited to calibrating models.

To this end, manufacturing assembly simulations are conducted and the resulting behavior should conform to known models. This validation study's questions are:

1. Does the task duration adhere to the established Wright learning model?
2. Can the established deterministic Wright learning model be extended to a probabilistic one using a dynamic gamma distribution?
3. Can the Risk Index model (previously used to predict the risk of injury), be applied to estimate the chance of defective assemblies?
4. When assembling component, do similar joints produce similar assembly errors?

Note that these questions have little to do VR. We use these research questions as a proxy to verify the data produced from the simulations are valid and of high-quality, as shown in the Figure 2. This in-turn increases our confidence in the VR simulations as a means of measuring the human state.

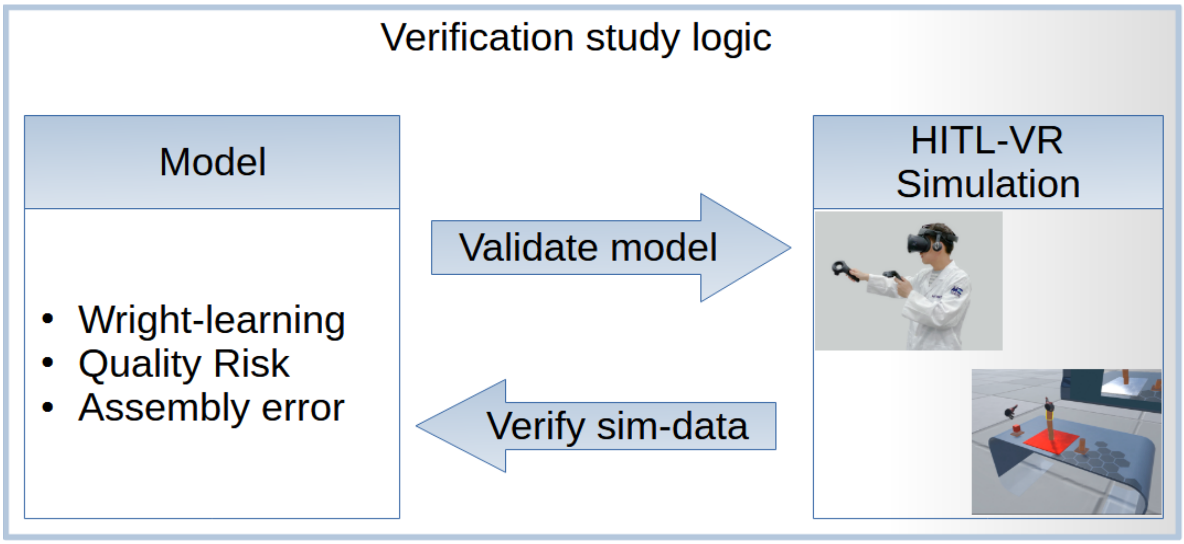


Figure x: The underlying rationale of this study lies in the concurrent validation of established models and the verification of the measurement technique.

2.5 Virtual assembly simulation

Several simulations were carried out, and the data was used for validation against the mentioned models. Subjects completed a series of tasks (placing, stacking, packing, and joining) commonly encountered in manual assembly. The task order is based on a subjective perception of increasing complexity, and although it wasn't randomized, it could have been. We opted for a fixed sequence of increasing complexity due to the novelty of virtual reality for many subjects, as complex tasks can be frustrating for beginners.

2.5.1 Task complexity

In order for a simulation to be considered complex, it should be valid for a range of assembly tasks. We describe task complexity with two discrete factors: cognitive load and sequential dependence. This description of task complexity is not meant to be exhaustive but rather illustrate the simulations capability.

We define cognitive load based on whether an assembly task is repeatable or random. In a repeatable task, the assembly schematic remains unchanged between repetitions, and the operator uses the same components for each repetition. These processes have low cognitive load. In contrast, in a random task, a new schematic is provided for each repetition, forcing the operator to interpret the schematic to select the appropriate components for assembly. These tasks have a higher cognitive load. Intuitively, tasks with higher cognitive loads should result in a higher risk of human error and, consequently, a higher quality risk.

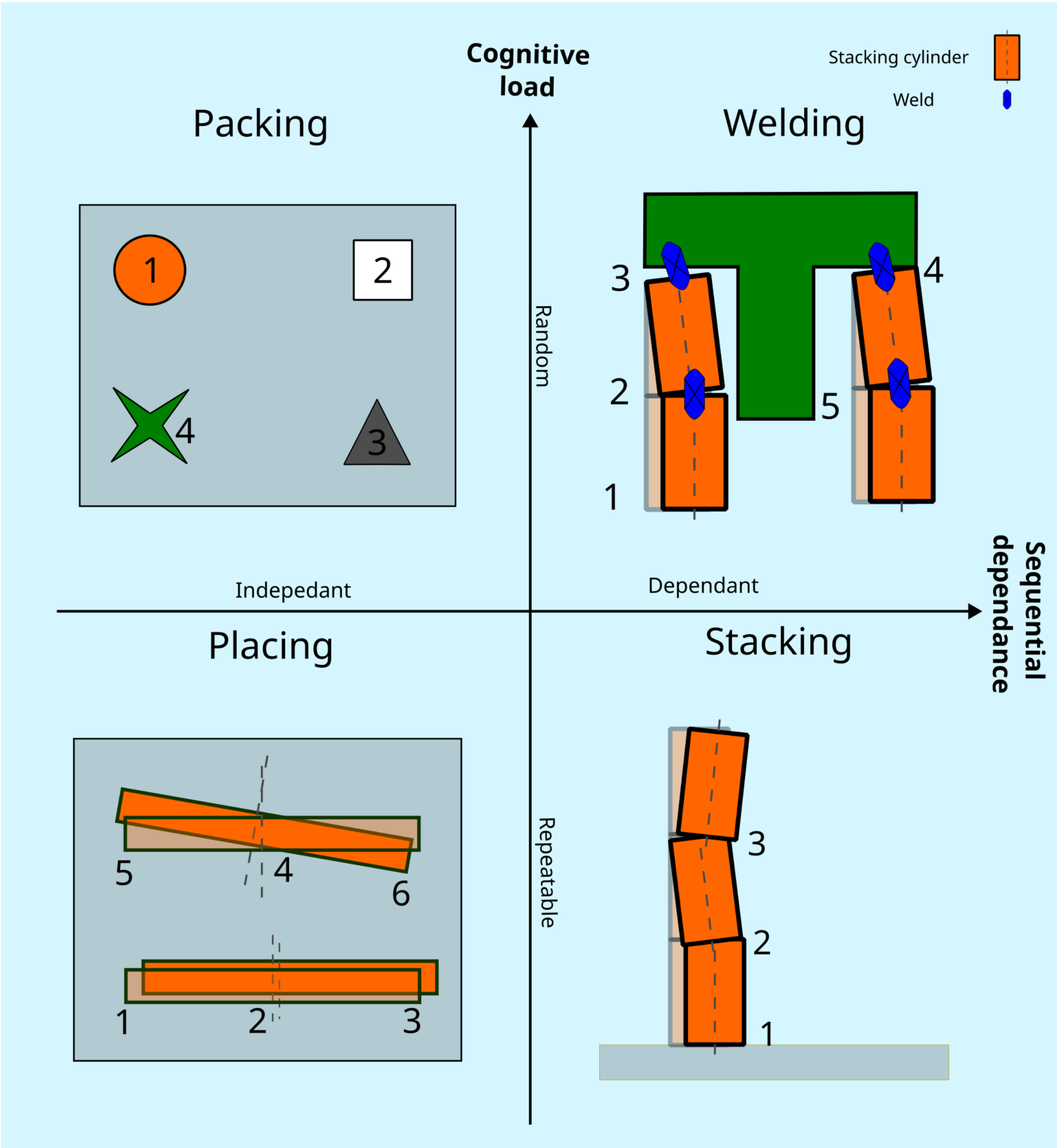


Figure x: Schematic Task Description Illustrating Task Complexity as Cognitive Load (Random vs. Repeatable) and Sequential Dependence.

Sequential dependence refers to whether the poses or placements of components are affected by the poses of subsequent ones. For instance, when stacking components, the pose of the previous component may influence the pose of subsequent components. An example of a sequentially independent task would be packing or assembling the legs of a table. In such cases, the pose of each component (legs) remains unaffected by the others. It was assumed that this would impact the assembly error. An unforeseen effect was that when an assembly appeared likely to fail, it was either discarded or reworked.

2.5.2 Task description

The four tasks involved subjects selecting components from magazines and placing them in desired locations. In repeatable tasks (placement and stacking) subjects were given one component type and placed it in demarcated areas. In the stacking tasks, refer to figure, subjects stacking three cylinders placing on top of the next.

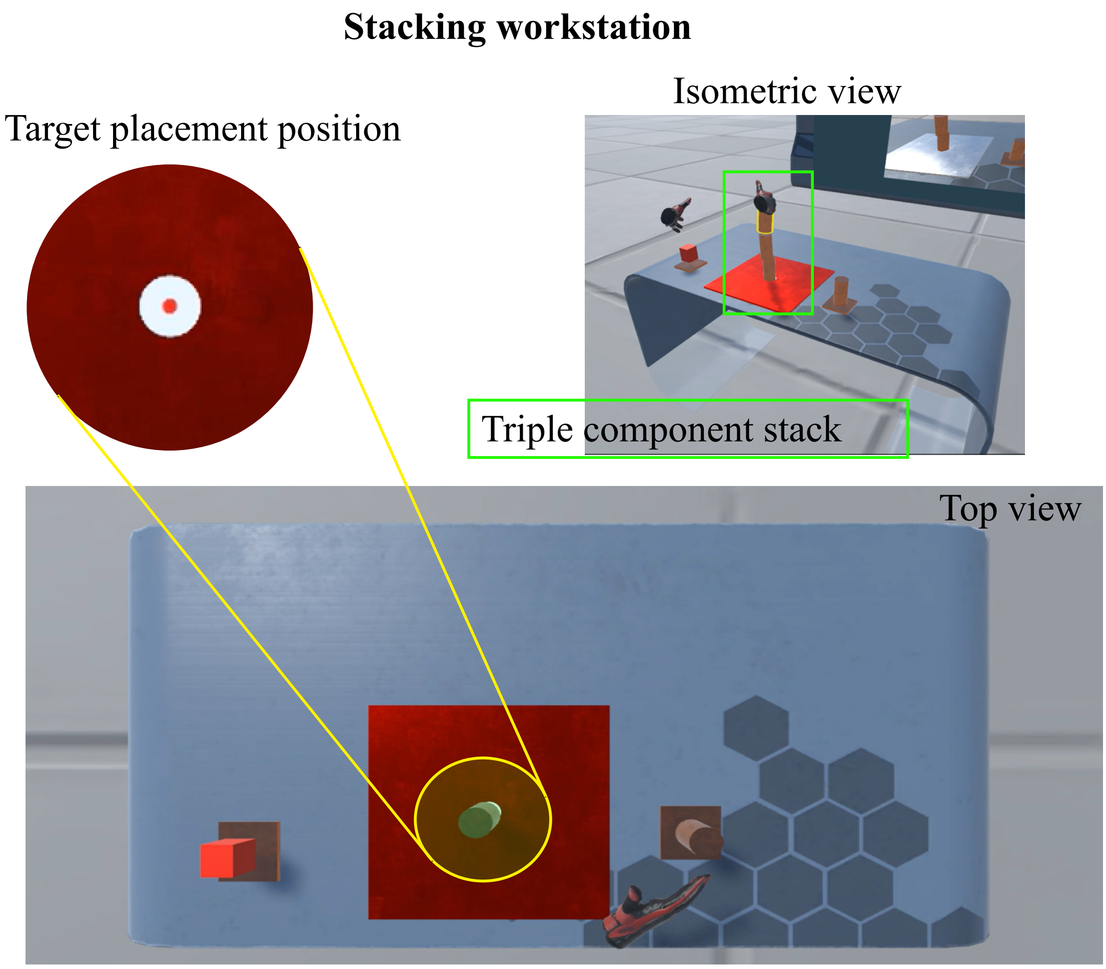


Figure x: The virtual reality simulation of the operator performing a repeatable task, stacking three cylinders.

In random tasks (sorting and joining), subjects are given a schematic and are required to select the appropriate components for assembly. Every repetition a random schematic is generated. The components are presented as primary shapes that correspond to assembly components cylinder, square-bar, triangular, and cross (X), refer to the figure below. In joining, five components are fixed (welded/tacked) together before submitting.

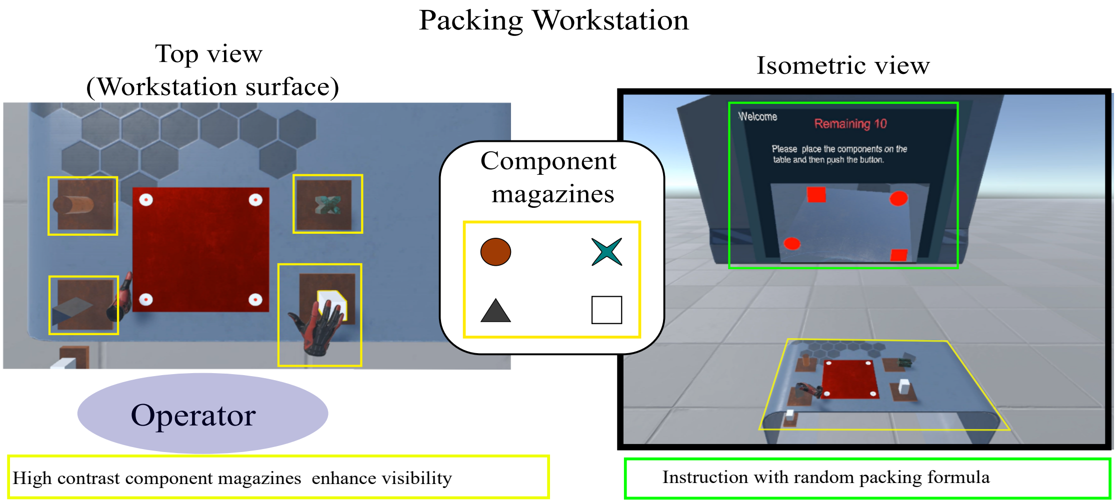


Figure x: The virtual reality simulation of the operator packing, involving identifying and selecting the required component.

2.5.3 Assembly error measurement

Using virtual reality we are able to measure assembly dimensions to a degree that would be impractical otherwise. Although we cannot expect this kind of data from physical industrial systems anytime soon, we may be able to gather insights that would otherwise be obscured. For example, one can quantify the assembly errors and use them to rank design alternatives [61].

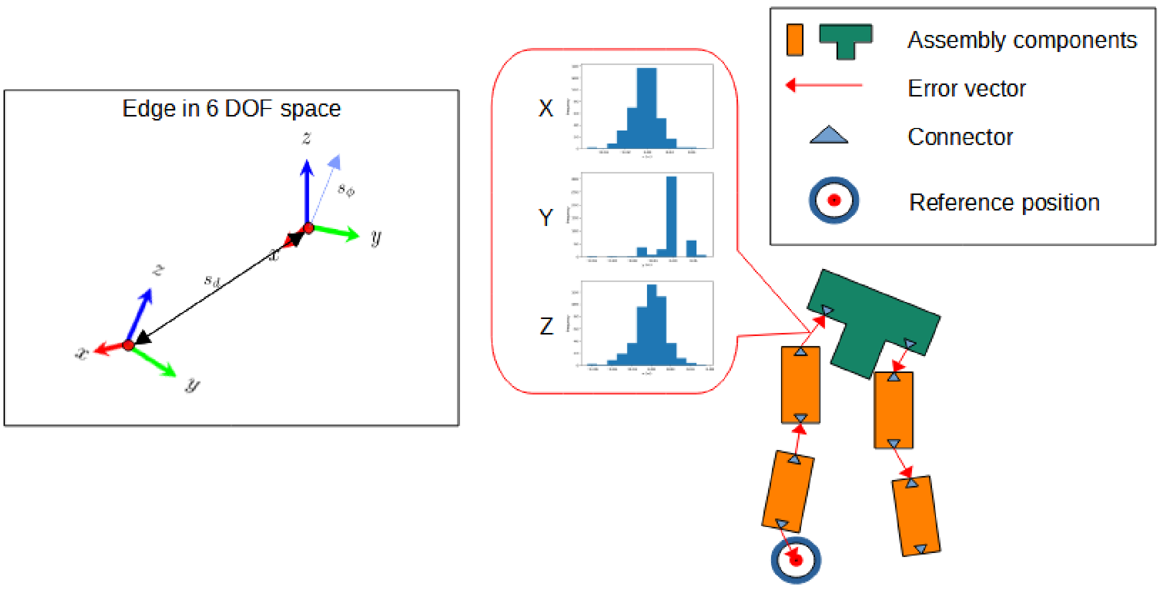


Figure x: The assembly errors as graphs consisting of components, connectors, and edges. These edges consist of probability distributions representing the distance.

In the simulation, the operator submits the completed assembly. It is transformed into a graph, with each component connector representing a node, and each connection representing an edge. This is done via a modified breadth-first-search where components are a collection of connectors, connectors are nodes, and connections between connectors are edges. The component types are checked against the schematic. The edges store the 3 DOF vector that quantifies the distance between connectors.

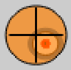
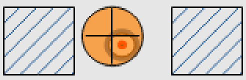
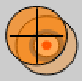
Joint name	Illustration	Task(joints)
Radial occluded alignment		1(1-6);3(1-4);4(1);3(1)
Biased occluded alignment		4(3,4)
Radial alignment		3(2-3);4(2,5)

Figure x: The assembly joint types

The graph's resultant edges are represented as vectors, with the displacements (x, y, z) being characterized by probability distributions. Please refer to the figure presented above for visual representation. The underlying hypothesis in this context posits that joints exhibiting similarity should exhibit similar probability distributions. By classifying wit a limited set of joint types, we can substantiated this hypothesis, demonstrating that analogous joints yield comparable errors when performing a given task.

All the joint types are present in the fourth task. Namely, the radially occluded joint (1) where target placement position is not visible under the profile (cylinder). Two radially aligned joints (2,5) where the profiles of components align. This has a more obviously perceivable error and therefore is expected to have lower assembly error than occluded joints. Finally, biased occluded connections (3,4) are skewed due to a nearby surface.

2.5.4 Experiment experience

Subject comfort was deemed more important than realism in this simulation. Since it was the first time most subjects had experienced VR, special attention was paid to the eligibility of text, placing components and buttons within reach, color and contrast as a means of communication, and selecting an appropriate number of repetitions for task. Pretrials involving other subjects used NASA-TLX surveys during development to highlight tasks for improvement. These NASA-TLX surveys were not recorded.

Objects are color coded to assist in communication. For example the submission button and submission platform are red. Task instructions are given in the form of a still image and text. For more complex tasks, schematic, video, and holographic model are shown. Audio and visual prompt informs them whether they have completed the task correctly. A completion bar illustrates their progress as to how many more repetitions need to be completed.

To block effect of subject height, the workstation height was calibrated based on the individuals limb length. Individuals assumed a series of poses and we calculated the limb length, using this to adjust the workstation. This hints that VR can be used to design ergonomic workstations without the need for actual hardware.

These features would not be available in a physical assembly simulation, but were necessary for the comfort of subjects.

2.6 Results

The purpose of the data analysis is to confirm that the data being obtained from these simulation represent human performance, thereby illustrating its suitability for measuring human performance. To this end, we conduct a validation study. By validating the VR simulation results adhere to the well-known model results, we verify the VR simulation is able to produce meaningful data. This shows the data acquired from VR can confidently be used in similar applications.

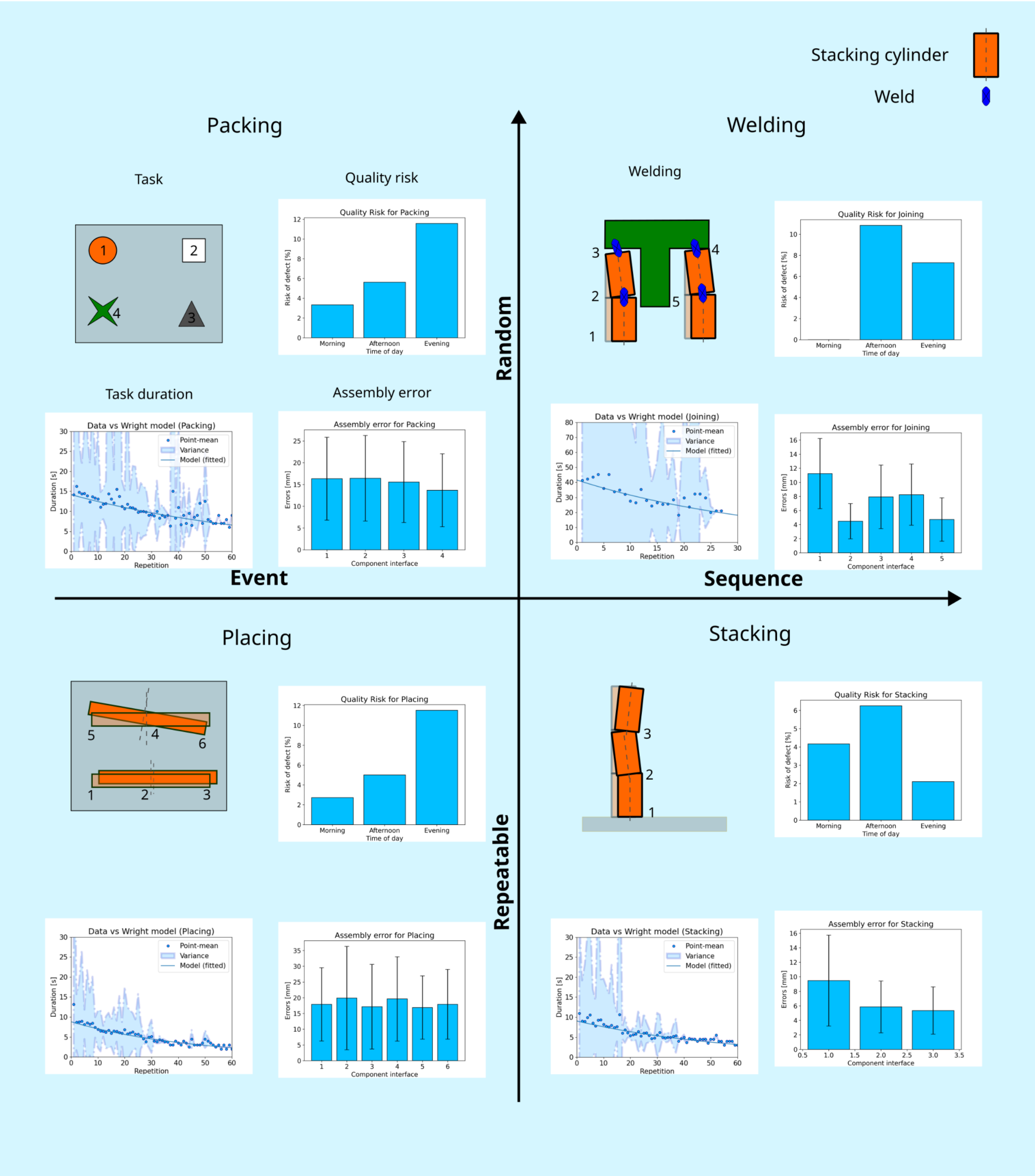


Figure x: illustrating the task schematic and results for the four assembly tasks simulated consisting of quality risk, assembly error, and task duration.

The figure presented above offers a comprehensive visualization of the results encompassing the simulation outcomes for the four tasks, showcasing task schematics, task durations, quality risk assessments, and assembly error data. Consequently, it serves as a central reference point that will be frequently alluded to in the subsequent text.

2.6.1 Wright learning

We begin our investigation by confirming that we can observe the established deterministic wright learning curve. We do so with a visual inspection confirming the mean follows the power law assume a normal distribution. As a Segway, we illustrate plot the variance, which leads to insights for establishing a probabilistic model.

The following figure vividly demonstrates how our simulation effectively captures data for observing the learning curve. By averaging the trial durations for each task, as depicted in the figure below, we can clearly discern that the mean duration closely mirrors Wright's learning curve for all four tasks. This consistent behavior across diverse tasks significantly bolsters our confidence in the simulation's results.

Notably, we observe that the durations converge towards incompressible work, although it's worth noting that the values of the learning rate and incompressible work vary by task. This suggests the necessity of conducting calibration experiments to ascertain the curve's specific characteristics for individual processes. These findings substantially enhance our trust in the virtual simulations. Moreover, delving into the variance provides us with even more intriguing insights.

We observe that initially, there is significant variance in task duration, which subsequently decreases as learning progresses. This pattern is consistent across all tasks. It's important to note that the final task, having half the repetitions of the others, exhibits less variance reduction. This observation across diverse tasks prompted an investigation into the possibility of achieving predictable variance.

2.6.2 Quality risk

In this analysis, our objective is to examine the impact of time-of-day on defect and quality risk within assembly processes. We observed that sequentially independent tasks (Tasks 1 and 3) yielded highly similar results, closely resembling the reference model. This similarity is characterized by two key findings:

Firstly, a discernible trend emerges, demonstrating an increase in risk as the day progresses. Notably, the morning exhibits the lowest risk, followed by increments in risk during the afternoon and evening. These results reinforce the validity of our simulation, as they align with the patterns seen in the reference model.

Secondly, the quality risk values for these tasks exhibit a similar pattern, with risk percentages ranging from 2% to 4% in the morning, 4% to 6% in the afternoon, and so forth. It is important to recall that the reference model employs relative risk, using the morning as the baseline with a risk value of one.

In contrast, the behavior of sequentially dependent assembly tasks does not conform to the predictions of the reference model. We suspect that rework may be a contributing factor. When future work depends on current work, operators are more likely to detect and address defects or opt for assembly rework. This behavior was observed multiple times in Task 4.

The results suggest that task complexity is being simulated. We observe that sequentially independent tasks adhere to the quality risk index model, while sequentially dependent tasks do not. On the other hand, cognitive load had no effect on the quality risk. This could be attributed to the practice of reworking assemblies that are likely to fail. It demonstrates a non-linear interaction between task complexity and the validity of the risk index model, which was detected through a complex simulation. More generally, this illustrates that task complexity has been successfully simulated.

In summary, sequentially independent tasks align with the reference model, whereas dependent tasks deviate from it. This unexpected outcome, considering that the reference model was initially developed for assessing injury risk rather than defects, has significant implications. Firstly, it bolsters our confidence in the simulation's ability to measure cognitive effects on human operators, given the consistency in results across tasks. Secondly, the fact that sequential tasks do not conform to the reference model and exhibit variability among themselves suggests that the model may oversimplify these tasks, highlighting gaps in our understanding.

These findings underscore the utility of these simulations in providing valuable data. Firstly, they indicate that the risk index, originally designed for injury risk, can be effectively applied to assess quality risk. This is economically significant, given the profound impact of quality and defects on the assembly of complex products. Consequently, this encourages the argument that human factors play a crucial role in manufacturing system performance. For instance, it supports the idea of implementing quality-conscious scheduling, allowing us to quantify the quality benefits of scheduling tasks in the morning versus later in the day. This holds particular relevance in mixed manufacturing systems, where optimal scheduling can enhance efficiency by prioritizing high-cost or intricate assemblies during the earlier hours and lower-cost, less complex ones later in the day. More broadly, these findings suggest that these simulations can be employed to investigate the influence of cognitive fatigue on overall performance.

2.6.3 Assembly error

The results of this study reveal a clear relationship between the similarity of joints and their corresponding error distributions. Visual inspection was employed due to the evident distinguishability among these joints.

In each task, the outcomes can be readily explained. For instance, in stacking, joints 2 and 3 exhibit radial alignment and similar distributions, while joint 1 is occluded and distinctly different. In the context of placing, the central points yield similar results, as do the edges. The welding/joining task serves as a prime example of clear differentiation among the three types of connections. These findings unequivocally demonstrate that similar connections yield similar distributions.

This outcome enhances our confidence in measuring assembly error through a logical classification of joints, followed by a visual assessment of quantified error distributions. The applicability of this approach to all four tasks bolsters our confidence further.

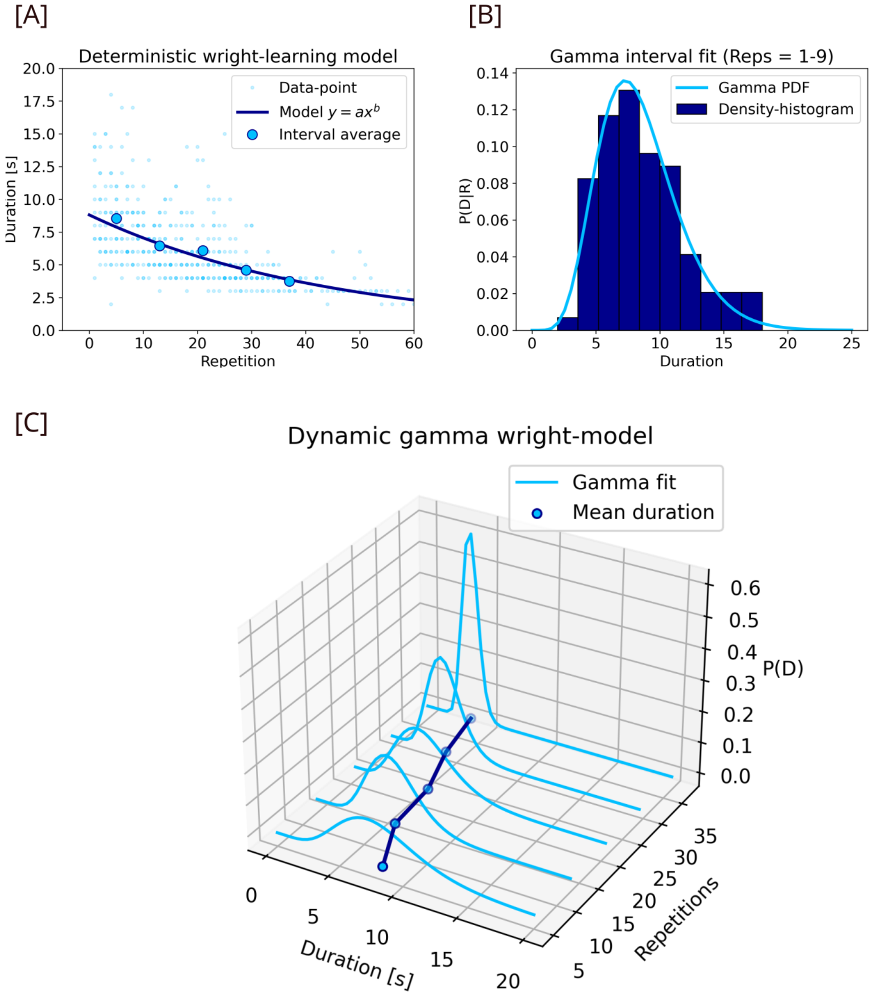
These findings once again underscore the motivation for virtual assembly. The use of a structured graph to store assembly error data is a valuable contribution, as acquiring such data outside of a virtual environment is impractical. Hence, the combination of data acquisition through VR and the granular storage of assembly error in a graph holds promise for exploration, particularly in suggesting design enhancements for current assemblies. The structured graph of complex assemblies can be utilized algorithmically to suggest connections with the highest error contribution, potentially warranting redesign or consolidation. However, the novelty of this method necessitates concrete validation against real-world assembly results. Moreover, it should be noted that these joints or connections represent only a subset of manufacturing tasks, excluding those involving fasteners, thereby limiting its scope. The field of graph-based virtual assembly error quantification is in its infancy and requires extensive development before confident adoption can occur.

On the other hand, these results bolster confidence in the capacity of virtual reality (VR) to simulate human performance and assess assembly errors. They also underscore the creative potential of virtual reality assembly and its applicability in novel ways to enhance existing product assemblies or inform design decisions.

2.6.4 Probabilistic wright learning curve

When we model task duration as a random variable, we observe that tasks are more likely to take longer than to be completed more quickly than the incompressible work duration. This behavior aligns with the characteristics of event duration and is typically represented using a gamma distribution.

Upon fitting a gamma distribution to the data, we notice that the dynamic-gamma model performs well for lower repetitions but exhibits a sharp decline in performance as repetitions increase. We evaluate the goodness of fit using Chi-squared scores and find that the gamma distribution aligns well with the model for lower repetitions but sharply deviates as repetitions increase. We suspect that the sharp drop in the Chi-squared score is associated with the decrease in data density, a known characteristic of the Chi-squared test. Notably, this outcome surprises us because, to the best of our knowledge, no previous attempts have been made to model Wright learning as a random variable. This model holds the potential to enhance scheduling models significantly by accommodating variance and incorporating confidence intervals.



[D]

Interval	shape	scale	μ	χ^2	#points	low-Rep	high-Rep
1.0	7.32	1.15	8.44	1.0	91.0	1.0	9.0
2.0	10.32	0.62	6.35	1.0	77.0	9.0	17.0
3.0	6.92	0.87	5.99	0.56	77.0	17.0	25.0
4.0	10.87	0.41	4.5	0.0	50.0	25.0	33.0
5.0	30.81	0.12	3.65	0.0	24.0	33.0	41.0

Figure x: Depicts the transition of the Wright learning model from deterministic to probabilistic for a single task. The average duration closely follows the Wright learning curve [A]. Gamma distributions are applied to intervals [B]. The resulting dynamic-gamma Wright learning model closely resembles the deterministic model [C].

The diminishing variance offers valuable insights into the learning process, stemming from two sources of variance within the data: inter-operator variance and intra-operator variance. The inter-operator variance, as shown below, represents the mean difference in trial duration per individual. Initially, the variance displays significant disparities in task duration, but after a few trials, subjects tend to converge towards a similar mean duration. One plausible interpretation of this figure is that individuals may start at different performance levels, but learning tends to converge toward a more consistent performance over time. Conversely, the intra-operator variance represents the variability in performance across repetitions by the same individual. This outcome could be interpreted as individuals experimenting with various strategies at the outset, resulting in higher variance, before eventually adopting a dominant and more consistent strategy. However, it is essential to exercise caution when interpreting these results, considering the potential influence of limited data and data density. Therefore, further investigation of this topic is warranted in the future.

Remarkably, prior research has not explored the concept of a probabilistic Wright learning curve, as far as we are aware. This inclusion holds two significant implications. Firstly, the incorporation of confidence and uncertainty recognition enables more informed calculations, scheduling, and decision-making processes. Secondly, the utilization of simulation and sensitivity analysis enriches our models, while ongoing considerations of epistemic uncertainty and newly acquired data facilitate continuous refinement of model performance.

In summary, the simulation results demonstrate that the dynamic gamma Wright learning model exhibits a strong fit in the early stages of learning, but its goodness of fit deteriorates rapidly as learning progresses. We attribute this phenomenon to limitations in the simulation data. Nevertheless, these findings carry substantial significance because the probabilistic Wright learning model surpasses its deterministic counterpart by quantifying schedule risks, thus enabling more informed decision-making. In addition to providing mean task duration and learning rate insights, this deterministic model does not offer this level of risk assessment."

2.7 Conclusion

In conclusion, the results of our comprehensive validation study provide compelling evidence of the suitability and efficacy of virtual reality (VR) simulations for measuring human performance across various tasks. Through a meticulous analysis of diverse aspects, we have gained valuable insights into the capabilities and limitations of these simulations.

Firstly, our investigation into Wright learning curves demonstrated that VR simulations can effectively capture and replicate human performance dynamics. The consistent alignment of mean task durations with Wright's learning curve across different tasks reinforces our confidence in the reliability of the data generated by the simulations. Moreover, the observed convergence of task durations toward incompressible work, albeit with varying learning rates, highlights the need for task-specific calibration experiments. These findings not only enhance our trust in VR simulations but also shed light on the complex interplay between task complexity and learning.

In the realm of quality risk assessment, our study revealed intriguing patterns related to the impact of time-of-day on defect rates. The alignment of sequentially independent tasks with a reference model, along with the observed deviations in sequentially dependent tasks, underscores the simulations' ability to measure cognitive effects on human operators. This discovery has significant implications, suggesting that these simulations can be used to assess quality risk and inform scheduling decisions in manufacturing systems.

The analysis of assembly error distributions provided further evidence of VR's capacity to simulate human performance accurately. The logical classification of joints and visual assessment of error distributions for various tasks demonstrated the feasibility of this approach. This not only enhances our confidence in measuring assembly errors but also opens up possibilities for design improvements and error reduction in complex product assemblies.

Lastly, the introduction of a probabilistic Wright learning curve model, despite its limitations in fitting the data, presents a novel avenue for incorporating confidence and risk assessment into scheduling and decision-making processes. This model's potential to quantify schedule risks adds a valuable dimension to our understanding of human performance in dynamic environments.

In summary, our validation study reaffirms the value of VR simulations as a reliable tool for measuring human performance across a range of tasks. These simulations offer insights into learning dynamics, quality risk, assembly errors, and even the potential for probabilistic modeling. While challenges and areas for further research exist, the results presented here underscore the promise and potential of VR simulations in enhancing our understanding of human performance in various domains, from manufacturing to decision-making processes.

Furthermore, these findings not only have significant implications for the domain of manufacturing assembly but also hold the potential to be valid and applicable in industries where human performance is critical, such as medical surgery, military operations, and various other sectors reliant on human decision-making and precision.

Moreover, the approach of complex operator simulation through HITL virtual reality exhibits considerable potential for its application in human-centric design, particularly in high-stake scenarios where human performance is paramount such as medical surgery, military operations, manufacturing processes, and mining operations.

2.8 Data collection and processing

While data processing is essential for replicating the results, it has been relegated to an appendix as it is not a prerequisite for comprehending of this paper.

2.8.1 Experiment procedure

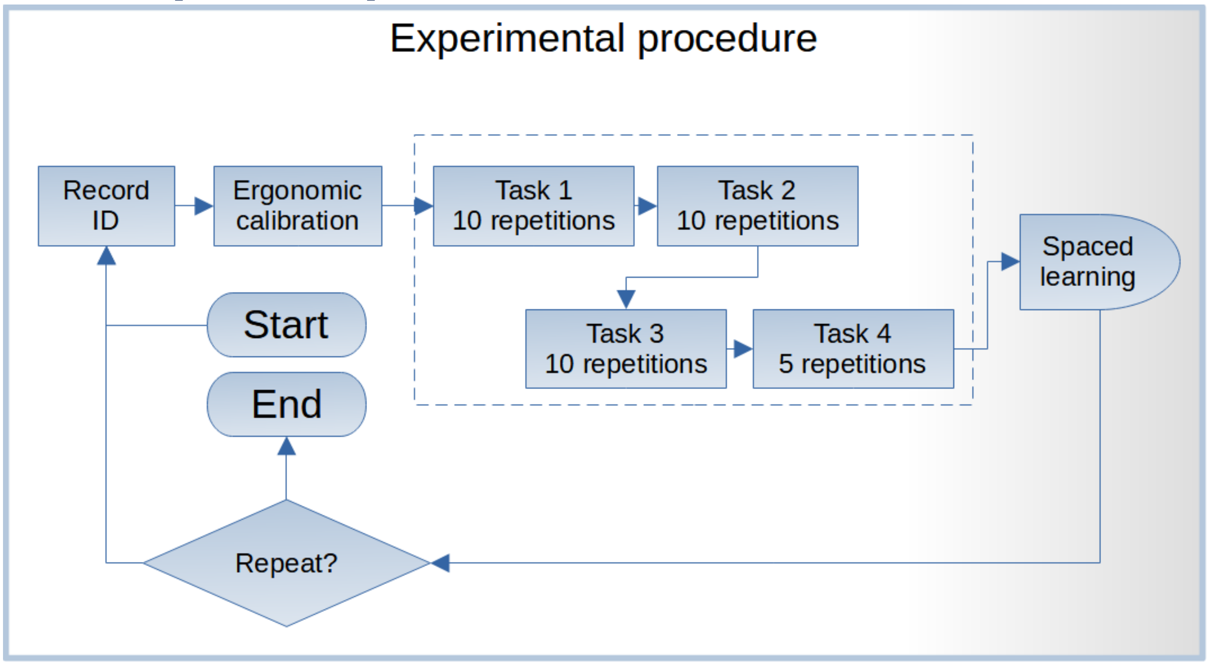


Figure A1: The experimental procedure flow diagram

Subjects completed up to 7 trials over the span of five days. Trials were spaced randomly, with a minimum 5 hours space between trials of the same subject. All subjects were between the age of 20-30[1]. There were 11 males and 1 female who took part in the study[2]. Not all subjects completed 6 sequential trails. The table below shows the frequency of trails completed. All recipients had little previous exposure to using VR. No compensation was given for this experiment.

In trials for task's one, two, and three subjects completed 10 repetitions (assembling 10 components). In task 4, subjects only assembled 5 components due to the duration and challenge of the final task.

In this trail we assumed spaced-learning, where subjects had a period between each trial, usually a day. We where faced with a single-case where one subject was available for only one

1 There tends to be a substantial mature population in manufacturing, not represented in this study.

2 This is not an unusual distribution of sexes in manufacturing environments.

day and decided run 4 trials on one day. The results were inconsistent with those above and therefore we removed this subject from the trial.

2.8.2 Wright-learning

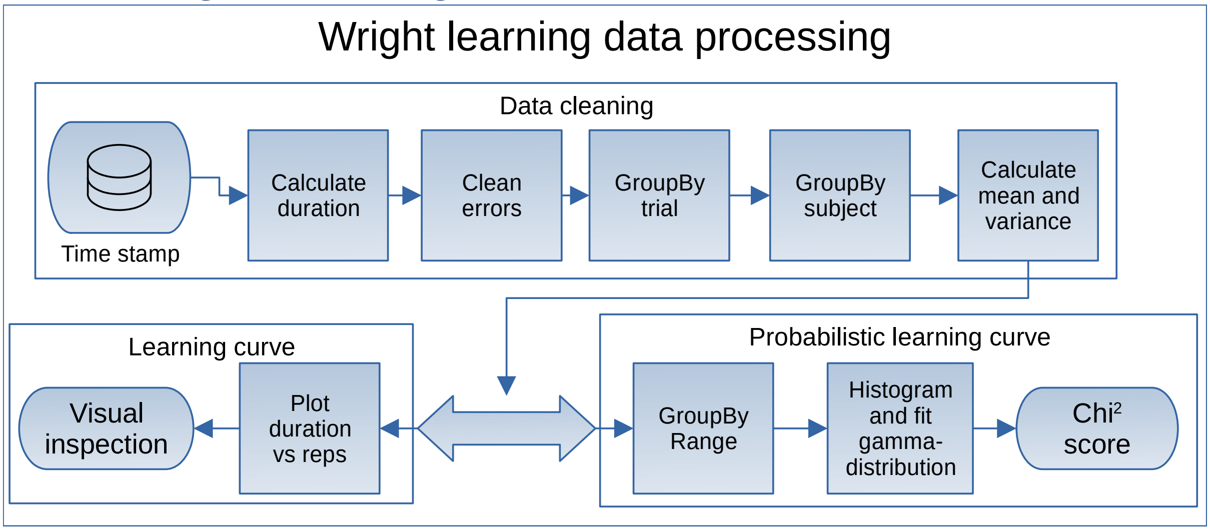


Figure A2: Wright learning data process flow for deterministic and probabilistic learning curve

We evaluate whether wright learning can be observed during the simulated tasks. We do so by evaluating the duration of tasks for different trials. Recall that each trial consists of 10 repetitions (except the final task which is 5 repetitions). We only use data from the 6 subjects that have completed 4 or more trials here.

2.8.3 Quality risk

Taking data from the same simulation, discrete errors occurred when the incorrect number of components or the incorrect type of components where assembled.

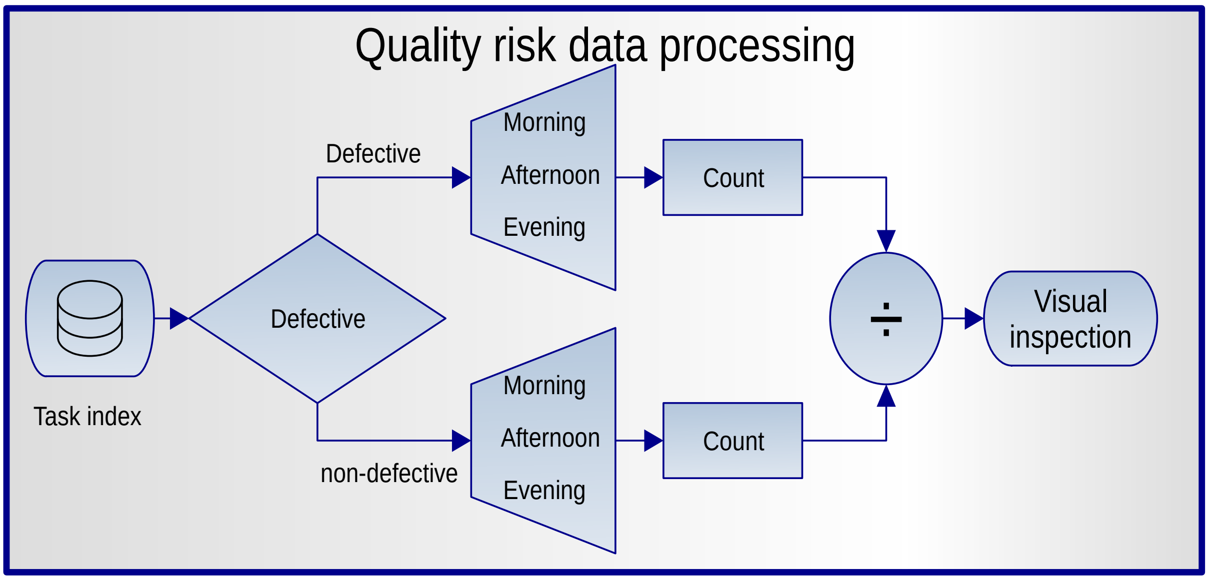


Figure A3: Quality risk data process flow

We compare the ratio of defective assemblies to non-defective ones, for 3 periods morning, afternoon, and evening. Where morning was session ended when the cafeteria served lunch (11:30 AM), and the evening session was chosen based on social behavior (After 14:00).

2.8.4 Assembly error

Our final analysis investigates assembly error. The assembly error quantifies the dimensional difference between a reference design and the assembly. This concept is fairly novel as it is not easy to achieve without this simulation. Hence, applications of assembly error may be limited.

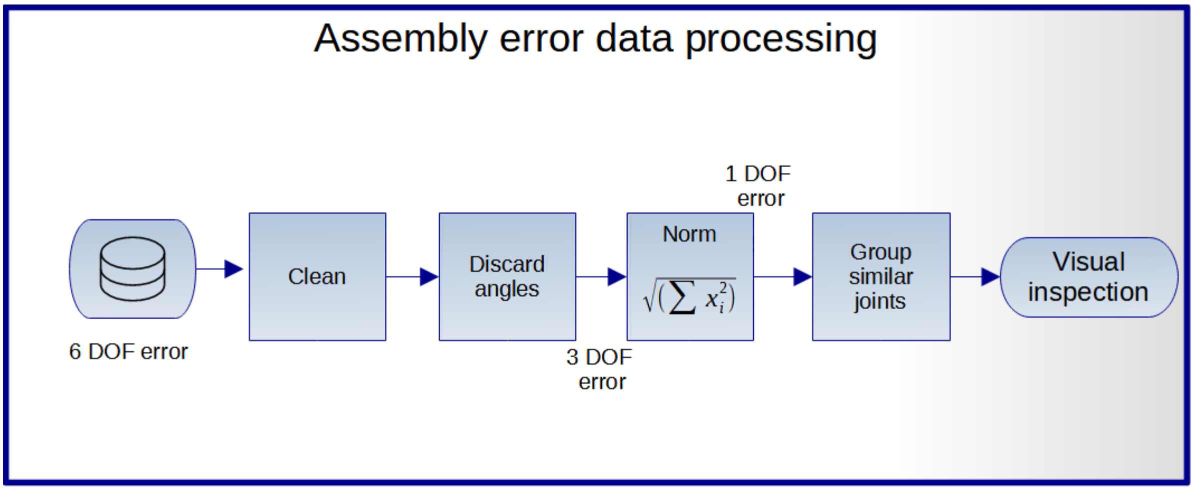


Figure A4: Assembly error data vectors are transformed into a radial distance as a normal distribution

The assembly error quantifies the distance between connection. We assume this to be an indication of the difference between the reference/ideal position and the actual position. Therefore a high error will result in an undesirable assembly.

2.8.5 Data collection

Defective assemblies occurred when a subject placed/stacked the incorrect number of components, or placed the incorrect component for a recipe. Errors did not count toward the repetitions in a trial, so if 2 errors occurred in a 10 repetition trial, the two error reps are repeated, totaling 12. The duration of a task is measured from the completion of the previous task till the completion of the current task. This means that (n-1) duration are available for n repetitions.

Number of Trials	Subjects completed
2	1
3	5
4	4
5	0
6	1
7	1

Table A1: The number of trails completed by subjects.

2.8.5.1 Data gathered

During each trial we collect the following data.

Field	Description
id of recipient	A unique number used to identify the subject. Used for data processing.
the duration of each repetition	The duration of each assembly task. Measured in seconds.
the time of day	The time of day that the task was started. Measured in seconds.
the day/date	The day of the week and date of the task.
the task being executed	One of the four assembly tasks being executed.
Error in assembly dimensions	An array of the error-dimensions (x,y,z, and angle) per component connector are recorded if the correct assembly was submitted. If the incorrect assembly was submitted an error was recorded (error/success).

Table A2: The data collected from each repetition

3. Deep active-learning based model-synchronization of digital manufacturing stations using human-in-the-loop simulation.

3.1 Abstract

The effective and accurate modeling of human performance is one of the key technologies in virtual/smart manufacturing systems. One challenge is obtaining data, here virtual reality (VR) has the potential to make human manufacturing experiments more practical.

In this paper we propose a framework to simplify human assembly task modeling. This is achieved by using VR to prototype data-acquisition systems for human manufacturing tasks. An active learning model is employed to reduce the number of experiments conducted by intelligently selecting the experimental conditions that will yield the most informative result. The resulting system requires less experimental trials and is automated. In VR experiments involving throughput rate, a deep active learning model significantly reduces the amount of data required, thereby speeding up the experiment and modeling process. The proposed method can quickly generate human performance models in virtual systems and improve experiment scalability. Previous data from a similar assembly task may be required for parameter tuning and design choices.

Keywords – Human-centric manufacturing; Digital twin; Virtual reality (VR); AI and machine learning; Virtual manufacturing; Digital transformation.

3.2 Introduction

Modern manufacturing systems include physical, data-acquisition, and simulation components. Human integration has been identified as a key factor impeding adoption [32], [33], [97]. There has been a desire to move towards human-centric production for years [47], [48], [91], but modeling human performance is complex. Recently interest in this area has seen a dramatic increase, with several special issues [40], [44], [98] dedicated to including humans in manufacturing systems, motivated by an EU report [38] placing human-centric production as a core value of Industry 5.0.

Human workstations are becoming increasingly “smart” to improve the productivity and effectiveness of operators. [43] identifies Human-centric assembly and Mixed reality as key areas for future development. Developing these stations can be costly as they need to consider ergonomic and cognitive load, while employing sensors, human-machine interfaces, VR/AR systems, etc. For this reason, virtual manufacturing and digital twin for a human process is an active research topic [27], [99], [100].

This work investigates prototyping human workstations for assembly tasks using Virtual Reality (VR). One issue that arises with virtual human workstation experiments is the cost of human labor in human-in-the-loop (HITL) simulation can be significant, particularly for skilled artisans. Therefore, this work investigates reducing the amount of human labor required to model the workstation's performance using an active learning model.

Combined VR and active learning allow rapid prototyping and modeling of manufacturing workstation performance, while reducing the risk due to sensor complexity and initial investment by allowing systems designers to gain performance metrics early in the design process.

The structure of this paper is as follows. The literature review (chapter 2) provides background on active learning, mentioning related work. Chapter 3 covers the experimental design, where: a VR simulation generates data, and a data-sampling experiment illustrates data efficiency. Chapter 4 covers the theory where sample selection is formulated as a search problem. Chapter 5 reports the results of the simulation and shows that utility-based sampling significantly reduces the number of trials. Finally, in Chapter 6 we discuss the outcomes of the application. The remainder of this chapter serves to briefly introduce the framework and its components.

3.2.1 Framework overview

The figure that follows illustrates the intended application of the framework. The idea is to implement a digital twin prototype before implementing the physical workstation, thereby reducing financial risk and resulting in a better final implementation. To fully exploit this virtual workstation, we employ deep active learning to reduce the number of experimental trials required to model the station's performance. This results in a smart digital twin of the process, consisting of a virtual workstation and a model for predicting the workstation's performance.

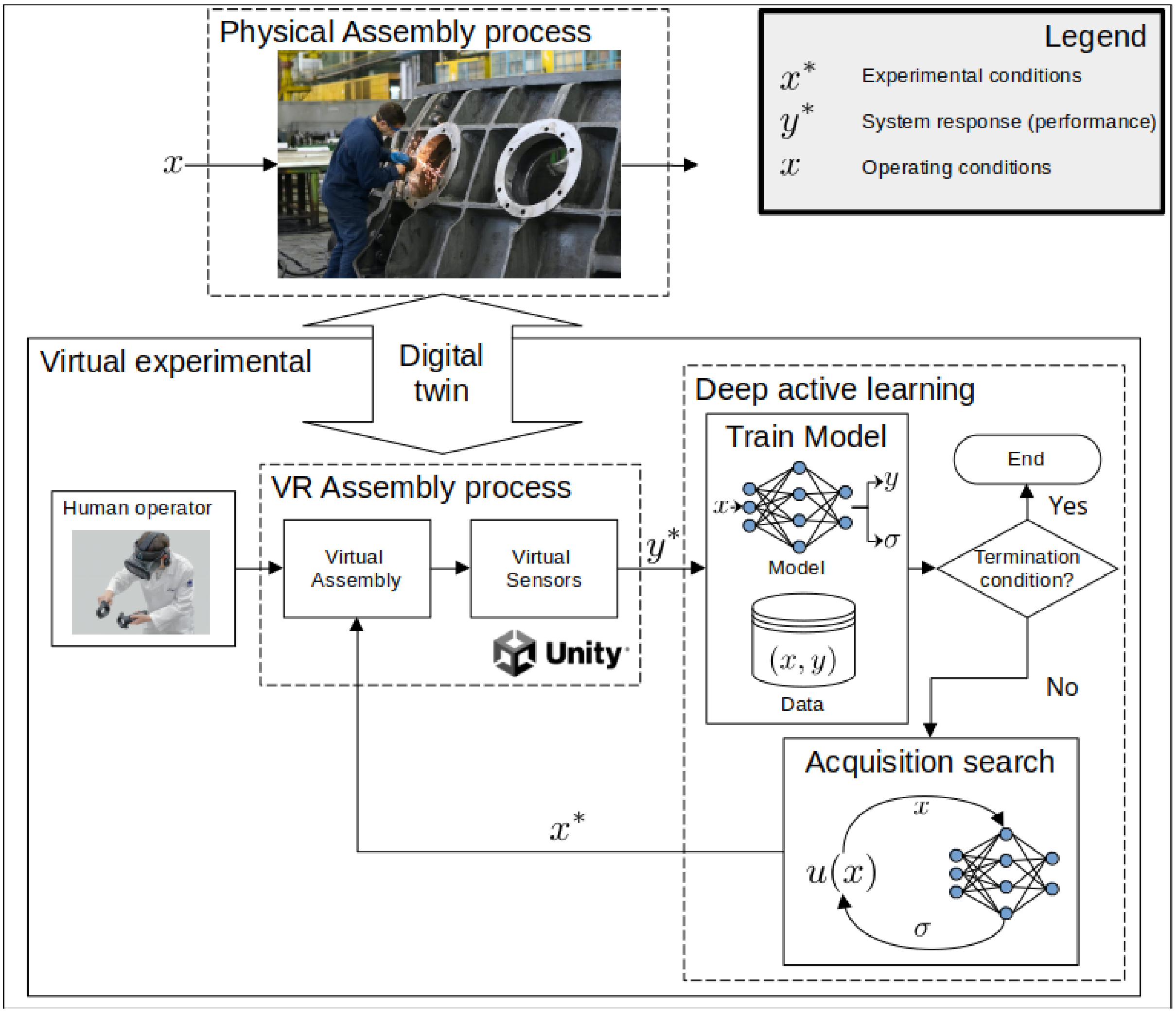


Figure 1 The proposed framework uses a virtual manufacturing process and deep-active learning model to perform HITL simulation. Note that these virtual workstations produce input (operating condition) and output (response) data.

The virtual workstation produces data. It records the system's performance (y) and measures the operating conditions (x) using a Virtual Reality HITL simulation. This method can thus be used to develop, reconfigure, and improve the workstation based on its performance.

The active learning model iteratively designs experiments by intelligently selecting the next trial. The models' objective is to acquire informative samples, reducing the number of trials needed to model the system. Once running, the model is trained every iteration until it satisfies the termination condition, concluding the experiment. The resulting model can be used for prediction.

3.3 Literature

Humans play a dual role in the manufacturing industry - they are essential for systems to remain competitive in a flexible environment with mass customization and mixed assembly lines [101] and serve as a strategic component of sustainable economic growth [102].

3.3.1 VR for Human data acquisition

Data acquisition is necessary for safety, prediction, and diagnosis estimation [36]. However, sensor placement for human tasks can be challenging. Industries with static operator tasks (long distance drivers and pilots) have found commercial success by placing sensors in chairs, steering wheels, operator-facing cameras, etc. [79]–[84], [86], [103]. However, in manufacturing wearable sensors are more common to accommodate the operators' task flexibility. Wearables often interfere with the operator's agency and comfort, inhibiting performance. Biological methods like oral swabs [19] are limited to model validation applications and are not practical for in-situ sensing.

An alternative to wearable sensors may be estimating the operator state from production output signals like throughput rate [104]. VR provides a means of delaying investment in hardware and sensors by digitally prototyping workstations while remaining useful for human-in-the-loop simulation data to validate models [105], product development [106] and visualizing and planning manufacturing systems and layouts [107].

To the author’s knowledge, two VR experiment frameworks are described in the literature [59], [108]. [108] provided a framework for planning experimental trials based on the selected factor, with the additional functionality of conducting remote experiments by storing data on a remote database. [59] developed a user-friendly framework for experimental design, requiring little knowledge of computer programming. Where both previous frameworks simplify experimental design, this work outsources the responsibility to an active model, resulting in an online automated experimental framework.

3.3.2 Machine learning for Human performance modeling

Human performance models (HPM) predict human behavior in a task or system. Given the complexity of human behavior, researchers develop simplified models that meet specific requirements. Historically, they used these models nto identify factors that affect performance, enabling ergonomists to design systems that optimize human performance [109].While computational models like ACT-R [110] were successful in predicting human performance, they require years of extensive programming experience, making analytical models more common.

Machine learning is a critical technology for the future of human smart manufacturing systems [111] because it uses data to automate model parameter tuning. However, it also comes with challenges related to data acquisition. For example, [52] used K-nearest neighbors to classify tasks according to skill level, facilitating hiring operators with the appropriate skills. Meanwhile, [112] used an Artificial Neural Network to model the relationship between the work environment, workers’ personalities, and their subsequent performance, although no quantifiable measure of the accuracy was provided.

The human factors methods community has recently shown interest in incorporating technologies such as artificial intelligence and big data due to the evolving nature of work [40]. For instance, [53] highlights the automatic extraction of insights from heterogeneous data (a capability of deep learning) and real-time data collection as key enablers of including digital human models in manufacturing Cyber Physical Systems (CPSs), both of which are addressed by the proposed framework.

In conclusion, human performance models were historically used to optimize performance in manufacturing systems. However, the emergence of machine learning and artificial intelligence can revolutionize these models. Real-time monitoring of operator behavior, automated modeling, and automated adjustment of machine settings are just two potential benefits. However, accurate data is critical for these technologies to be effective. While wearables can provide this data, they can also be uncomfortable or distracting for operators. As an alternative, VR experiments provide a controlled environment for gathering performance data, without the drawbacks of wearables. By leveraging these technologies and methods, manufacturers can achieve better optimization of human performance and increase efficiency.

3.3.3 Wright's learning curve

Wright's law, which predicts the falling cost due to cumulative production [30] using logarithmic/exponential functions ($y = a\,x^b$), has been used to predict the cost of silicon [113] and lithium-ion batteries [68], [69]. When Wright's law is applied to human production schedules, Wright learning predicts the reduction in task duration [70]. It later received numerous modifications considering work-induced fatigue, and rest schedules [70], [73], [75], [91], [104]. To the best of the authors' knowledge, all previous Wright learning models are deterministic, likely due to collecting average throughput data. Regions of high variance require more experimental data, which influences active sampling.

3.3.4 Intelligent sampling techniques

In this section, we mention previous work investigating data-efficient experiments and modeling. These are rooted in statistical methods and work by selecting the next experimental sample data point intelligently to reduce the number of experimental trials required.

3.3.4.1 Design of experiments

Where experimental design is concerned with the selection and blocking of factor-level combinations, the Design of experiments (DoE) builds on this by including a protocol for analyzing the data and selecting the next experimental sample [114]. DoE methods such as factorial design and response surface are well known and have their roots in statistics. These methods typically use linear regression models and are therefore limited to situations with few factors, few factor levels, and constant random error. Recently, iterative design [115] as shown promising results in optimizing the process operating parameters.

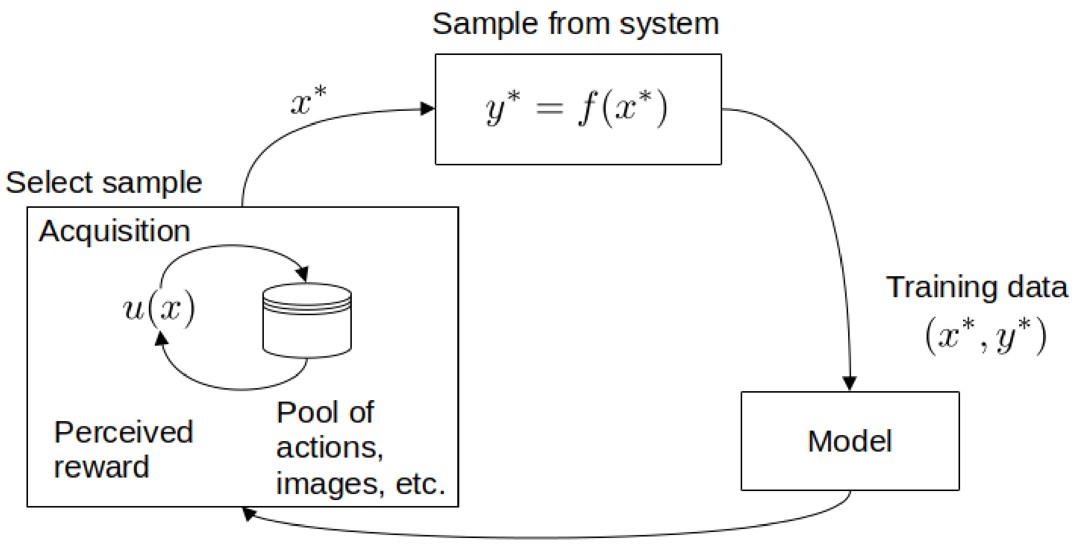
3.3.4.2 Reinforcement learning

The methods described in this section fall under the category of reinforcement learning. Recent reinforcement learning is primarily focused on overcoming non-trivial local minima in complex environments by making a sequence of decisions. For instance, [116] investigated a tightly related topic, “The design of experiment using reinforcement learning”, where they show a car could escape a bowl-shaped obstacle by driving around to build up momentum and then catapulting out. While reinforcement learning typically overlooks the cost of acquiring samples, often through simulation, this work considers the cost of acquiring the next informative sample to make the learning process more efficient. However, it is important to note that reinforcement learning is a general technique and is not always related to experimental design.

Reinforcement learning has been applied in unrelated work to search for optimal neural network architectures. This becomes particularly relevant in this context because, as the dataset grows from samples, two key challenges emerge. Firstly, as the dataset grows, the model may need to be updated to ensure continued accuracy. Secondly, given that the model is retrained every iteration, selecting architectures with shorter training times can provide a significant advantage. Where [117] highlights the ability to continue training as a desirable feature of some algorithms, [118]–[121] show that reinforcement learning can be used to optimize the model architecture at runtime.

3.3.4.3 Pool-based active learning

Active learning refers to having the model choose the next action. In pool-based active learning, the goal is to maximize the model's classification performance while minimizing the number of labeled samples needed [117]. This is particularly useful when gathering unlabeled data from the internet is easy, but the process of labeling it is expensive due to human effort.



	Acquisition	Sample
Reinforcement learning	State + Reward action selection	Perform action in environment
Design of experiments	Regression, optimization, etc.	Conduct experiment
Pool-based Active learning (classification)	Search through pool for sample	Human oracle labels

Figure 2: The relationship between active learning, reinforcement learning, and design of experiments, which all involve choosing the next action based on previous outcomes. In the discrete case, a pool of unlabeled samples are stepped through before selecting the next samples, while in the real-valued case optimization/search is performed.

Pool-based active learning for classification problems is by far more popular than experimental intervention, with modern literature equating active learning with classification [117], [118], [122]. There is comparatively less work considering regression [121]. The main difference between classification and regression in active learning lies in the selection of the next sample to acquire. In classification, an unlabeled pool is stepped through to select the next sample. In regression, a surrogate space is searched formulating it as an optimization problem.

Although these frameworks share similarities and use varying terminologies, each has a unique focus. Design of experiments optimizes processes by adjusting system response, reinforcement learning helps agents escape local minima, and active learning selects samples intelligently to reduce data requirements. As our goal is to reduce data requirements, we adopt the terminology of active learning.

3.3.5 Acquisition strategies

In pool-based active classification, an acquisition function returns a sample's usefulness and is used for selecting informative samples from the pool. Optimal experimental design [123] formalizes informative samples by selecting the next sample that equivalently minimizes the variance of estimators or contains the most information content.

The acquisition functions balance several concerns when selecting the next sample, these concerns are equally valid in classification and real-valued regression problems. One acquisition concern is selecting the sample with the highest expected model change [124]. Since the value of the sample selected is not known, a common heuristic is the variance computed from query by committee [125]. Another concern is diversity, as samples congregated around a small area will not be indicative of the general behavior. Evidential sampling [126] considers the geometric position of samples as a measure of uncertainty. [121] applies this to the regression prediction of driver drowsiness by selecting the next sample based on the centroid of the previous samples. [127] proposes passive sampling where the acquisition function is based on a separate (non-learning) model, not requiring re-training at each iteration, and achieving more stable performance by avoiding fluctuations from selecting samples with the highest regression errors.

This work contributes to the next generation of human-centric cyber physical systems [9], [36], [100], [128] by making experimentation and implementation of process modeling practical. Naturally, it also synergizes well with the digital twin paradigm by simulating and modeling workstation performance.

3.3.6 Preliminaries

This section contains the fundamental concepts and prerequisites for understanding active learning. If you are new to this field, we advise you to read this section carefully. However, if you are already familiar with the basics of active learning, you may choose to skim through this section to refresh your memory.

3.3.6.1 Model training and uncertainty

For effective sample selection, the model needs to predict the mean response (y) and epistemic uncertainty (σ), where epistemic uncertainty quantifies sparsely represented data [129] $(y, \sigma) = g(x)$.

Several techniques estimate uncertainty in regression models, Query by committee ensembles [125], [130] is the de facto and was used here. Other methods include Bayesian neural-networks [131], [132] bagging/bootstrap [133], dropout-techniques [134] and Gaussian process regression [131], [135].

3.3.6.2 Ensemble models

Ensembles are based on Query by committee [125] where multiple models predict the same value. The intuition is that if the data sufficiently describes the behavior, all models will predict the same outcome, the magnitude of the discrepancy in the prediction can be interpreted as uncertainty. The figure that follows illustrates this and indicates that sampling at regions of high uncertainty can benefit the model. The results are then combined to obtain the mean and variance [136], [137]. See [138] for a recent review.

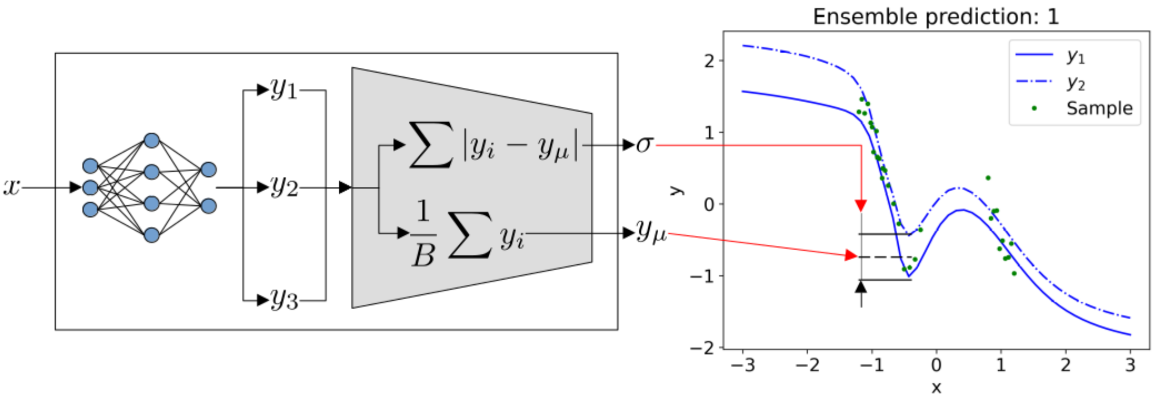


Figure 3 Ensemble uncertainty estimation. Here the ensembles attempt to predict the same value. The uncertainty is the distance between predictions. The mean prediction is the average of predictions.

The mean value and uncertainty can be found using the equations below, where B is the number of ensembles. The predicted-mean (μ) being the average of the ensemble-predictions (g_i), and the uncertainty being the distance between the mean and the ensemble-prediction.

$$\mu(x) = \frac{1}{B} \sum g_i(x)$$

$$\sigma^2(x) = \frac{1}{B-1} \sum \mu(x) - g_i(x)$$

3.3.6.3 Loss function

The loss function must now quantify the mean error and uncertainty. The well-known negative log likelihood [139] loss function was used with minor modifications. Gaussian noise is assumed.

$$L = \frac{n}{2} \left[\log(\sigma^2) + \left| \frac{y_\mu - y_t}{\sigma^2} \right|^2 \right]$$

3.4 Methodology

The experiment's aim was to show that active sampling will require less data than random sampling. To this end, VR simulations were conducted to gather data where human operators completed a series of assembly tasks. Next, a sampling experiment compares active and random sampling using the acquired data. Ideally, one would conduct one simulation using active sampling and another using random sampling. Instead, the data is reused in the sampling experiment. Wright learning was selected as the case study for the experimental task, where the goal is predicting the duration of an assembly task. Due to the sequential nature of task repetitions, the aim is to "Instead of having all operators perform maximum repetitions, intelligently stagger the repetitions between operators."

3.4.1 Virtual manufacturing simulation design

The experiment involved human operators performing common manufacturing assembly tasks. Several data fields were recorded, but only task duration was used in this analysis. An explanatory video is provided here. Subjects are required to place components in specific locations and an audio-visual prompt informs them whether the task was completed correctly. The task is performed for several repetitions. The task sequence culminates in the operator selecting components from magazines and welding them together according to a diagram.

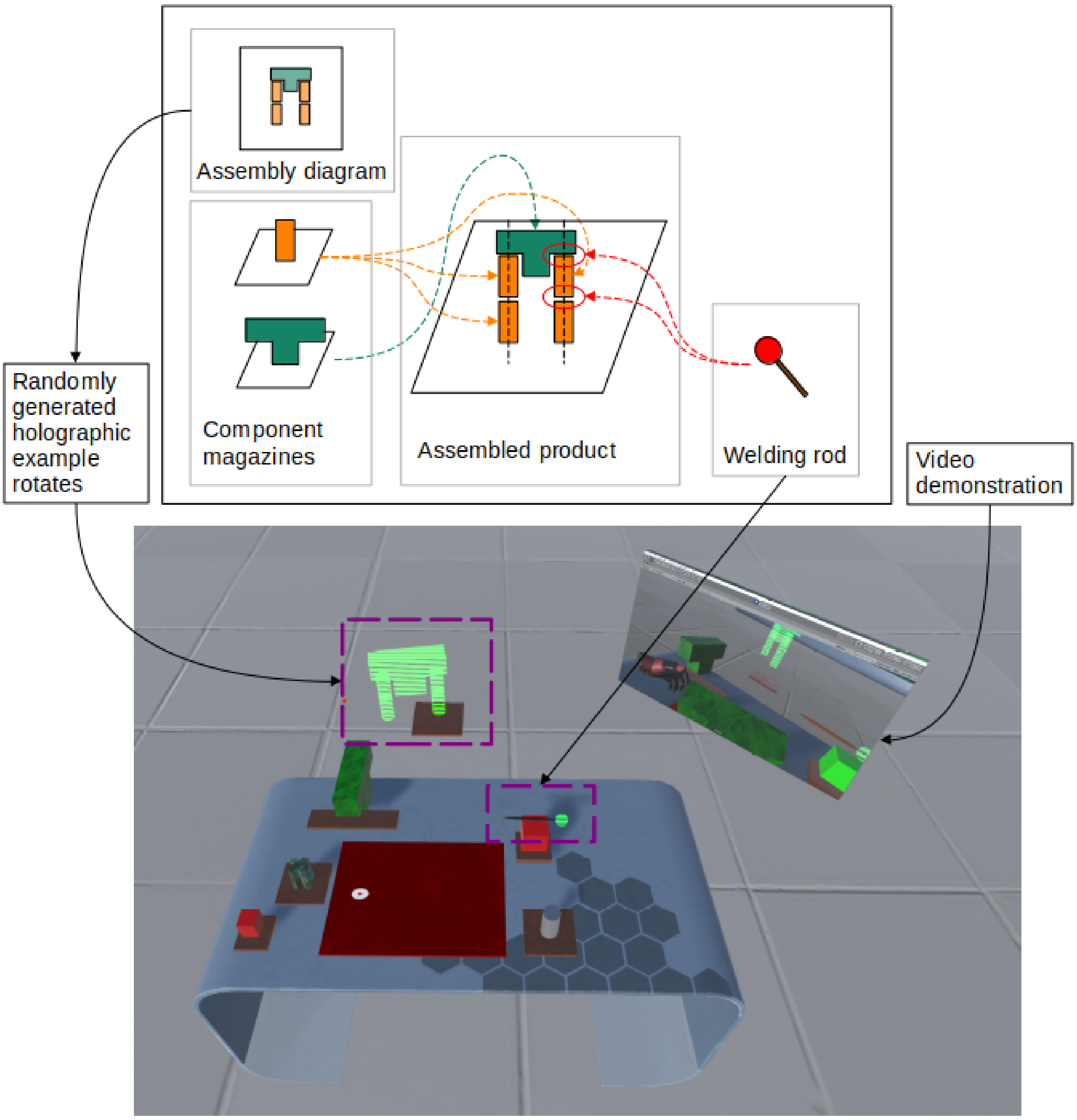


Figure 4 The final assembly task joining is shown schematically (above) and in VR (below). The operator selects components from magazines and welds them together. The final assembly is illustrated via a hologram.

We call these tasks: placement, stacking, sorting, and joining. We have a subjective notion of them increasing in complexity to aid first-time VR users in learning the tasks. We refer to this as the task index.

3.4.1.1 *Simulated task description*

To begin with, the placement task was scheduled first due to its simplicity, as it involved simulating repeatable pick-and-place operations. Following that, stacking was introduced, which required users to place one component on top of the other, simulating the effect of accumulated errors.

While the first two tasks are repeatable since components are moved to and from a predetermined location, the subsequent two tasks involved more complex processes that required the operator to follow a randomly generated schematic.

In the sorting task, the operator was provided with a schematic and had to select the correct components from magazines and place them in the appropriate position. The joining task involved welding components together from a small library to form an assembly. These tasks imposed a higher cognitive load on the subjects.

Therefore, it is important to consider the complexity of tasks when scheduling them in a specific order. Starting with simpler tasks and gradually increasing the complexity can help ease the operator into the work and build up their skills and confidence.

3.4.1.2 Experimental procedure

In a calibration phase the workstation table-height was adjusted based on the individual's limb length. Individuals assumed a series of poses allowing the calculation of the limb length. This blocked ergonomic factors between subjects which was particularly evident for taller individuals. This hints that VR can be used to design ergonomic workstations without the hardware. Similarly, during development, the workstation layout was configured to place components within comfortable reach of operators. Equipment and components were color coded to ease recognition.

In trials for placement, stacking, and sorting (tasks 1-3) subjects completed ten repetitions. In joining (task 4), the repetitions were halved due to the duration and challenge of the final task. Errors did not count toward the repetitions in a trial, so if two errors occurred in a ten-repetition trial, the two error reps are repeated, totaling twelve.

Subjects completed up to seven trials over five days. Trials were spaced randomly, with a minimum of 5-hour space between trials. Subjects were between the age of 20-30[3]. There were eleven males and one female who took part in the study[4]. Not all subjects completed six sequential trials. All participants had little previous exposure to using VR. The tasks were not explicitly explained to the subject, save for a video and an introductory tutorial. No monetary compensation was given for this experiment.

The VR environment was developed in Unity3D using the SteamVR plugin, custom C# code, and an HTC-Vive Cosmos head mounted display with controllers.

3.4.2 Sampling data experiment

The main objective is to reduce the number of experiments conducted. To do this we compare random sampling and active sampling. In active sampling the model selects the next experiment sample $x^{¿}$ based on an acquisition function, in random sampling $x^{¿}$ is selected randomly within the experimental range.

3 There tends to be a substantial mature population in manufacturing, not represented in this study.

4 This is not an unusual distribution of sexes in manufacturing environments.

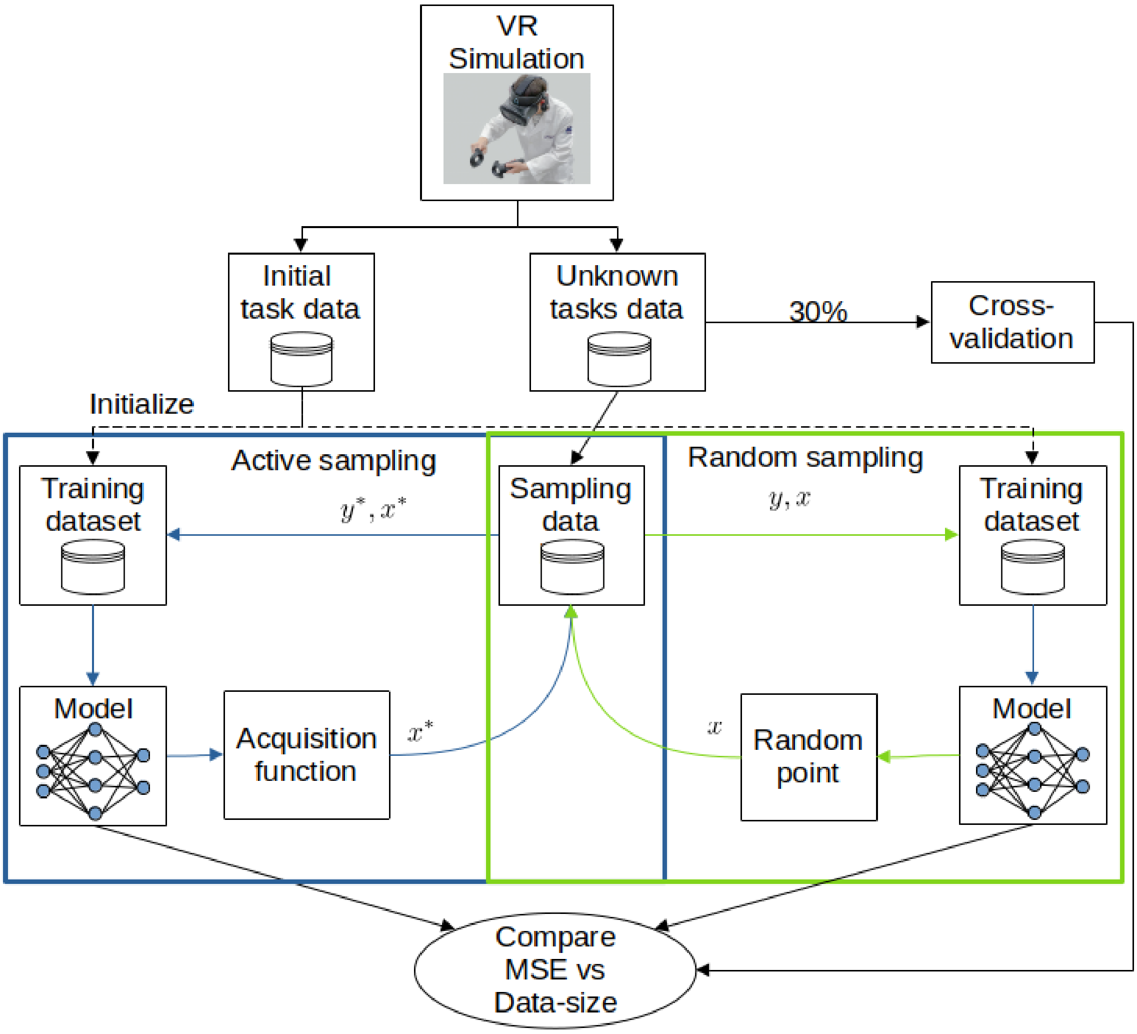


Figure 5: The sampling experiment design. The data is acquired from VR experiments and split into initialization, cross-validation, and data-bank sets, to compare active and random sampling's MSE.

The data acquired from the VR simulation is divided into three parts. Firstly, the initial task data is used to initialize the model. Next, a cross-validation dataset is separated from the three remaining tasks. Finally, the remaining data constitutes the sampling data bank used for random and active sampling. In the experimental loop shown above, both models select data from the sampling databank and append it to their training data. The difference is the active model uses informed acquisition, whereas the random model selects the sample arbitrarily using a uniform distribution. Finally, the MSE and training dataset sizes are compared showing which model performs better.

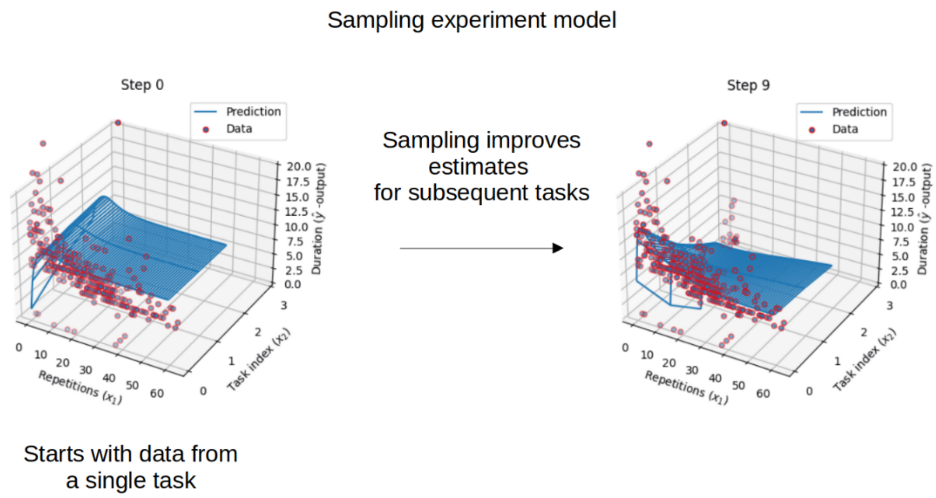


Figure 6: The intended experimental outcome is sample efficient estimation of task durations.

The model inputs are task index and the number of repetitions ($x \in R^2$) and the output is task duration ($y \in R$), which can be easily represented as a 3D graph. However, including additional inputs resulted in only marginal accuracy improvements, while significantly increasing the input space.

The Pytorch package was used for these experiments. For runtime deployment, Unity provides the Barracuda module [140].

3.5 Theory

3.5.1 Active learning model

The active learning algorithm used follows a straightforward loop. Starting at a selected initial point $x^{¿}$, it samples from the unknown system. Where $f(x)$ is the system being observed, $g(x)$ is our function approximating the system, which also predicts the uncertainty, $(y, \sigma) = g(x)$. Appendix A illustrates snapshots of this for an example function.

The sequence is as follows:

1. Conduct an experiment at $x^{¿}$, resulting in $y^{¿} = f(x^{¿})$.
2. Append the data to the training dataset.
3. Train the model using the current training pool.
4. Determine the next sample point $x^{¿}$.
5. Repeat this process until the termination condition is reached.

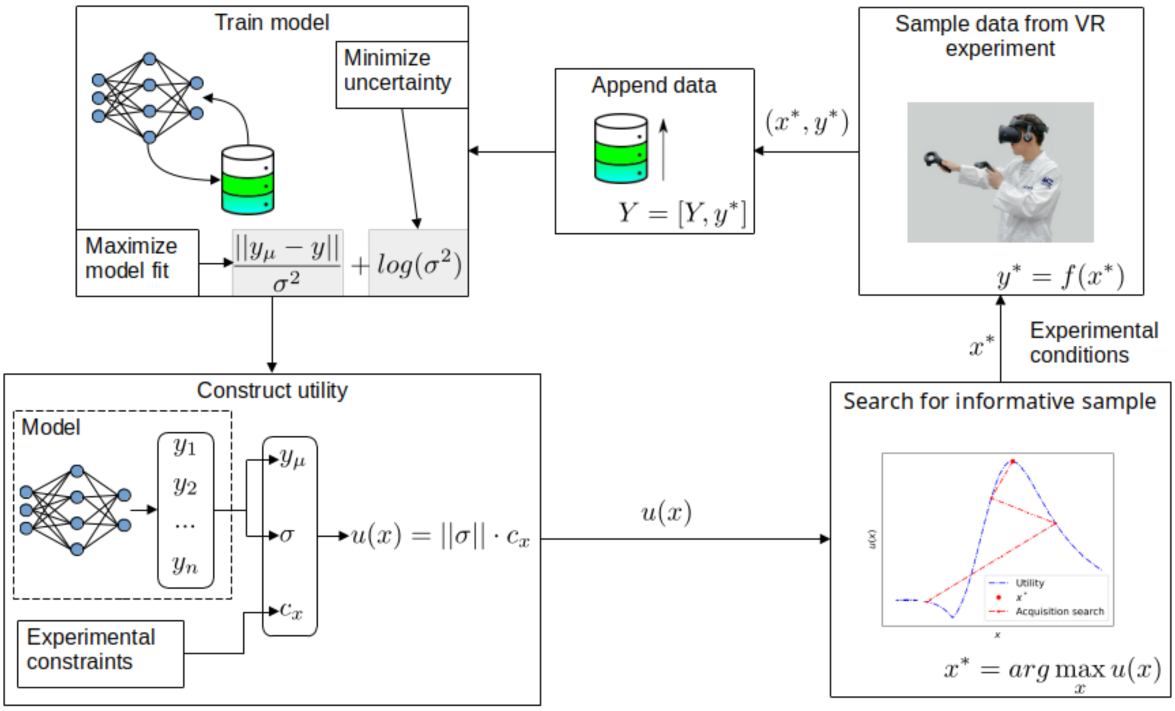


Figure 7: The main loop of the algorithm as applied in this work. The utility represents the acquisition function and is used to search for informative experimental conditions. It is constructed from the model uncertainty prediction and user designed functions.

3.5.2 Uncertainty estimation

In this work, a convenient (local) ensemble method inspired by [130] was used. It has two main differences from global ensemble methods. Firstly, instead of using multiple models, a single neural network has multiple mean predictions. Secondly, there is no need to split the data. This model is suitable as an entry point for ease of use, but we suggest other ensemble methods in practical applications. The figure below shows the two configurations.

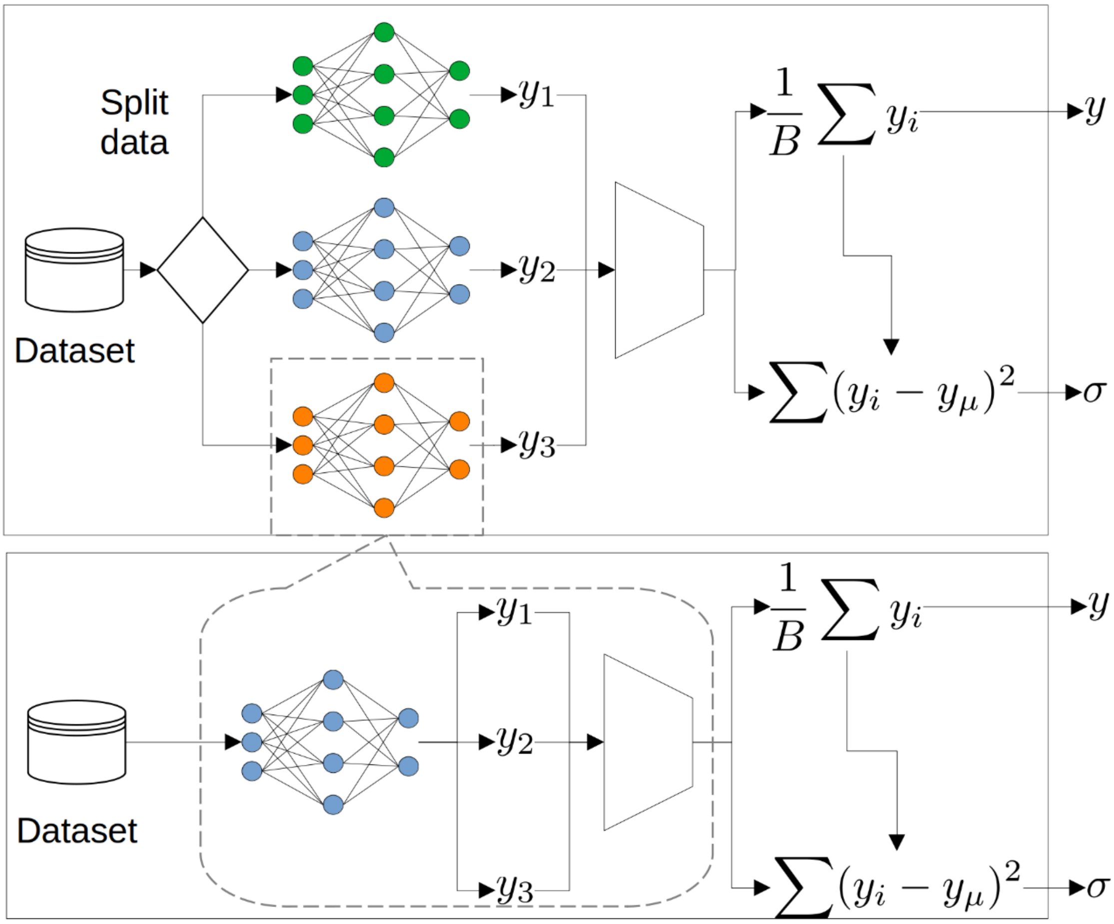


Figure 8: Ensembles predicting the mean response and uncertainty. Above, global ensemble methods train multiple models on random subsets of the data. Below, the local ensemble method trains a single model to make multiple predictions.

Note that local ensemble methods can be used within Global ensemble methods, hence the two are not exclusive. We do not claim that this method yields better results, and we suspect that this model will not scale well with dimensionality, number of ensembles, inputs, and outputs due to the interaction between neurons.

3.5.3 Utility based acquisition and experimental constraints

We formulate the selection of the next sample as a search problem, with the acquisition function acting as the objective function. Recall that the uncertainty σ is a real value defined as a norm of $\sigma(x)$ or $g_\sigma(x)$ and $x \in R^n$, where n is the input dimensionality. We also assume that all inputs are controllable. The optimization/search tools (Standard Gradient descent) are already present in the deep learning framework (Pytorch), making this a natural solution.

A naïve solution would sample where the uncertainty is the highest $x^{¿}=\underset{x}{argmax}(\sigma(x))$. This turns out to be a reasonable approach but does not account for experimental design constraints. Instead, we propose utility as a means of combining the multiple concerns of the acquisition function by biasing the model's selection, in turn retaining some control over the model.

Consider $Util(x)=\sigma(x)*c_1(x)*c_2(x)*\ldots$, where $c_1,..,c_n$ are constraint functions we design. The utility is shaped by multiplying these functions. We typically design these functions to be in a range of 0 to 1, e.g., $c_i(x)\epsilon[0,1]$. We now select the point with the maximum utility (instead of uncertainty) using optimization $x^{¿}=max(Util(x^{¿}))$. The figure below shows the use of step functions. One can see that due to our constraints on the maximum utility our sampling point will always occur within our experimental range[5].

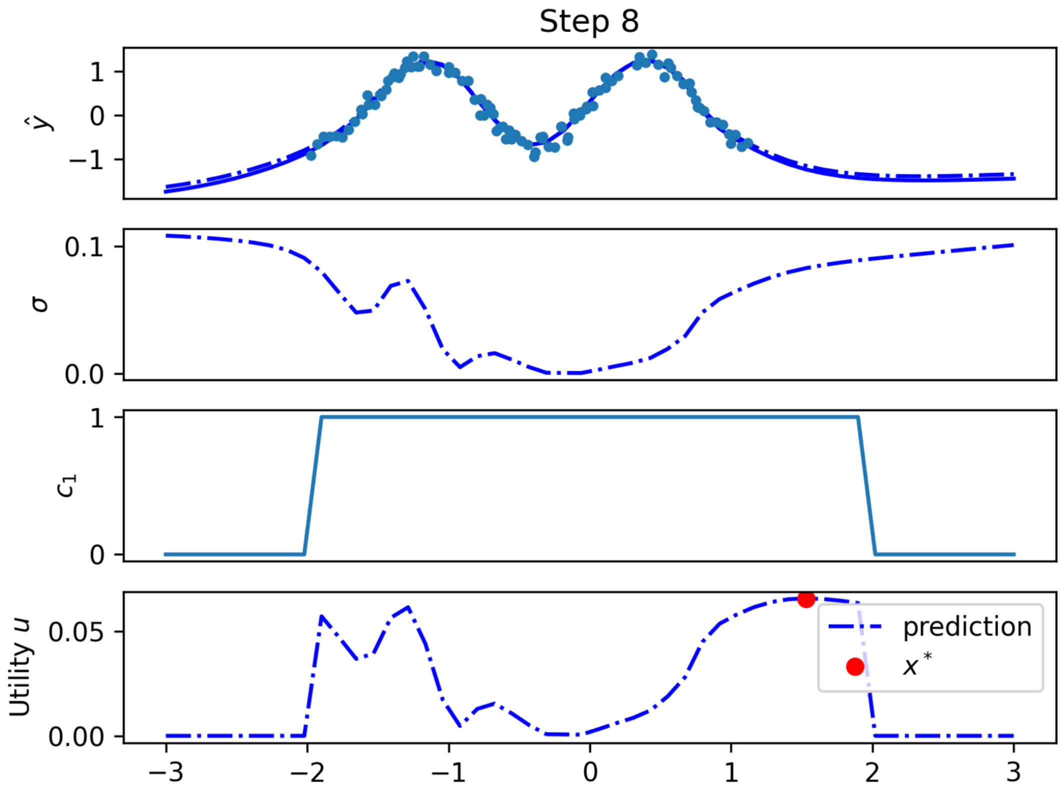


Figure 9: The construction of utility $u(x)=c_1(x)*\sigma(x)$ for an example $f(x)=\sin(4x)+q$. The step function c_1 constrains the selection of $x^{¿}$ within the experimental design range. The sample is selected by maximizing the utility, $x^{¿}=\underset{x}{argmax}(u(x))$.

An issue involving the algorithm stalling by sampling in the same region was overcome using these methods. Appendix 8.2 mentions additional acquisition constraints.

5 Excluding when the utility function or constraints are zero functions.

3.6 Results and discussion

3.6.1 Virtual manufacturing simulation

During the virtual assembly simulation, subjects performed four common assembly tasks and recorded the duration of each repetition. All four tasks showed similar results, with the mean duration following Wright's learning model. However, the model parameters (incompressible work duration and learning rate) differed across tasks, suggesting that virtual assembly effectively captures relative task durations, making the data valuable for human performance modeling.

Notably, the study does not directly verify the similarity between physical and virtual assembly durations. VR applications typically exclude tasks involving heavy lifting or long distances. On the other hand, it is a common practice to eliminate these tasks through automation or mechanization. This suggests that poor verification performance could indicate further ergonomic optimization, where virtual assembly can provide rapid reconfiguration.

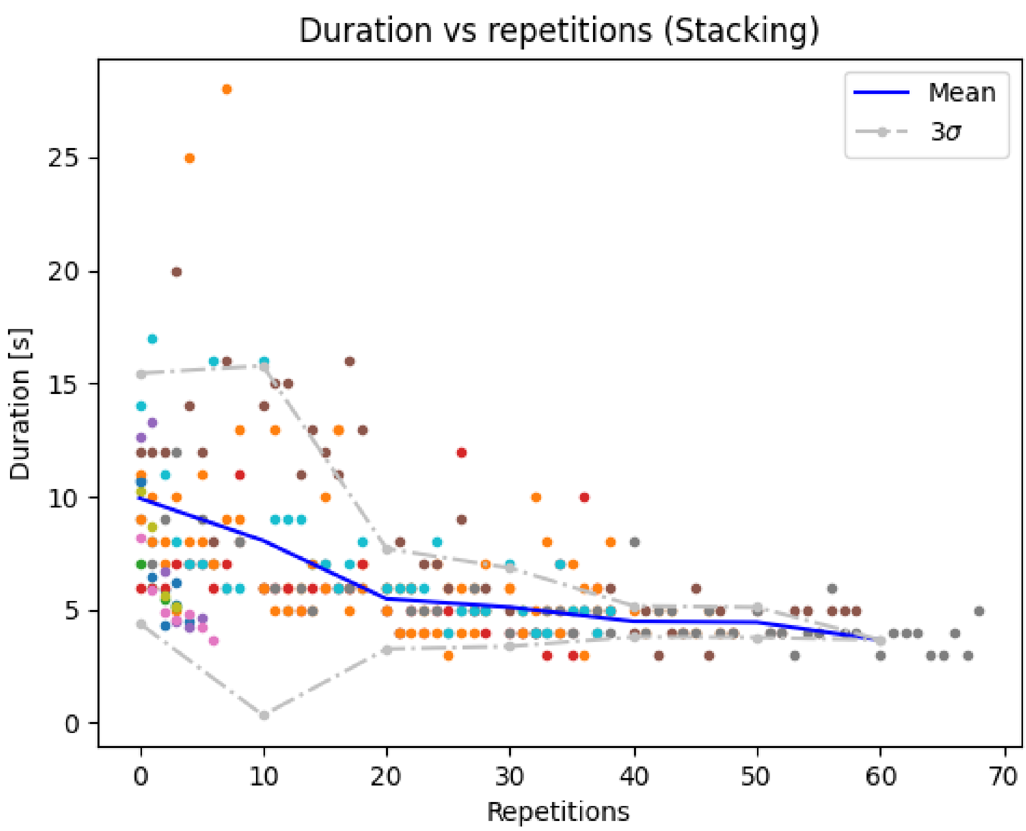


Figure 10 The durations for the stacking, the mean, and variance are taken across each trial (10 repetitions). The assorted color dots correspond to individuals' measurements. An operator is likely to have a task take longer than shorter, resulting in a skew distribution.

While all four tasks demonstrated mean durations following Wright's learning curve model, the variance also appeared predictable. Variance was higher during early learning (low repetitions) and decreased with more repetitions. This pattern held for both inter-subject and intra-subject (inter-repetition) variance, suggesting that operators begin at different levels but tend to converge towards similar performance with practice. The significance of variance lies in regions with higher data variance requiring higher sample density, which affects the amount of data needed for effective modeling.

Furthermore, the distribution of task durations exhibited a skew, leaning towards longer durations rather than shorter ones, resulting in a non-normal distribution. It's important to note that in our active-learning model, we assume a normal distribution despite this observed skewness.

The study's consistent results across dissimilar assembly tasks increase our confidence in the data produced from virtual assembly simulations. Furthermore, the observed variance provides valuable insights, indicating that mistakes are more likely to occur during early learning stages, resulting in longer task durations.

3.6.2 Sampling strategy

The learning noise, referred to as variance, has a significant impact on the amount of data required in specific regions. Additionally, the early stages of learning often hold less importance compared to the learning limit, which represents the steady-state task duration. Our objective now is to construct an acquisition function that models performance with fewer samples, showcasing the mitigation of high-noise regions and the flexibility of acquisition functions.

The figure below presents strategies to avoid unnecessary sampling caused by high-noise regions in Wright's learning variance. The traditional uniform sampling strategy results in many subjects completing numerous repetitions, making it inefficient. Alternatively, an uncertainty-based strategy allocates more samples in high-noise regions and fewer samples in low-noise regions. Here, subjects complete varying repetitions, with the number of repetitions decreasing over time.

When the learning limit is the primary interest, a utility function can be employed to disregard the high-noise regions, further reducing the required samples, and resulting in fewer subjects performing multiple repetitions. However, this tradeoff is that the model may not accurately predict regions of low interest. This example demonstrates that the acquisition function can be tailored based on the intended use of the model. In our case, we successfully determined the learning limit with fewer samples, leading to reduced experiment time and cost. Nevertheless, we acknowledge that this may come at the expense of accurate predictions in regions of low interest.

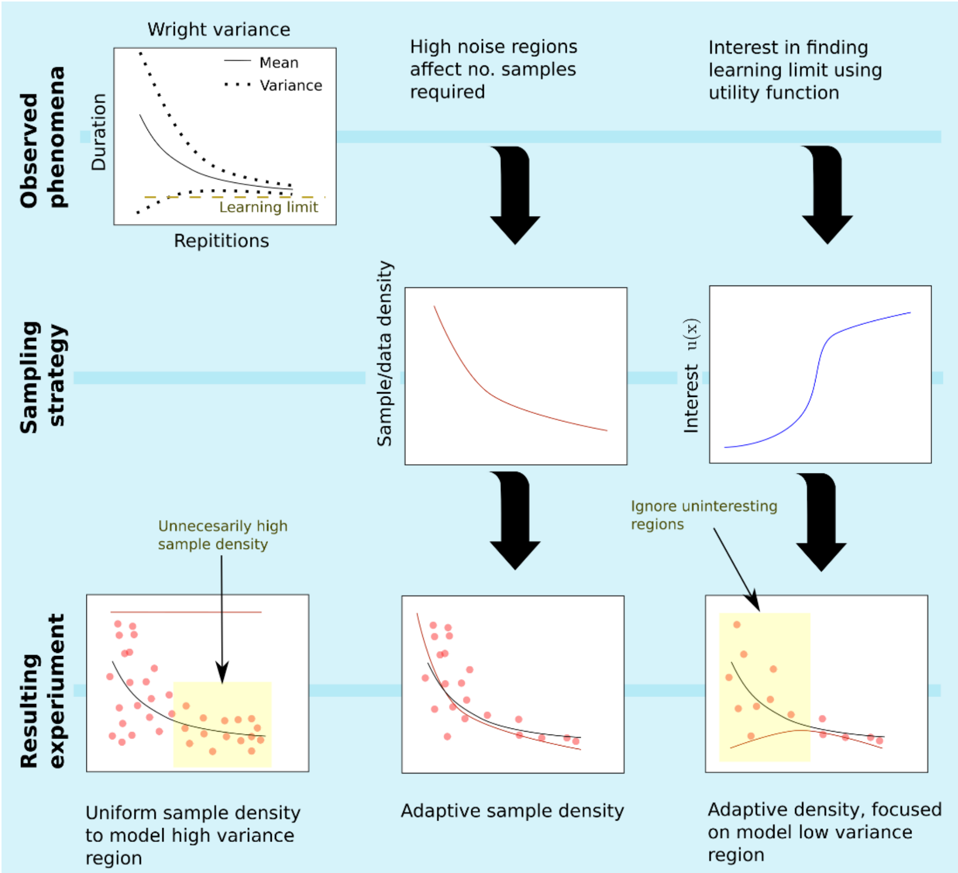


Figure 12 Some possible outcomes of active experimental design for Wright learning, where (left) simple strategies sample unnecessary data, (center) an uncertainty strategy samples adaptively, and (right) a utility sampling strategy captures the learning limit of the task duration.

3.6.3 Sampling experiment

A sampling experiment was conducted to compare active and random sampling strategies, with random sampling representing a uniform sampling approach. The experiment aimed to quantify the efficiency of each sampling strategy in terms of Mean Squared Error relative to the number of data samples.

In this study, simulation data was utilized to identify the phenomena of learning variance and develop a mitigation strategy. One suitable use case for active learning is efficiently data-enriching the model with data from previous tasks to reduce the error. However, it's important to note that active learning is limited to situations where we have knowledge of the model behavior, not necessarily its parameters, or where data from a similar process is available. These reasonable assumptions prevent blind application of active learning on unknown processes.

The results are presented in the figure that follows, illustrating that active learning significantly outperforms random sampling, achieving lower error rates with fewer samples. The Mean Squared Error (MSE) resulting from active learning exhibits a random distribution due to the model's random initialization, but statistically, active learning dominates random sampling.

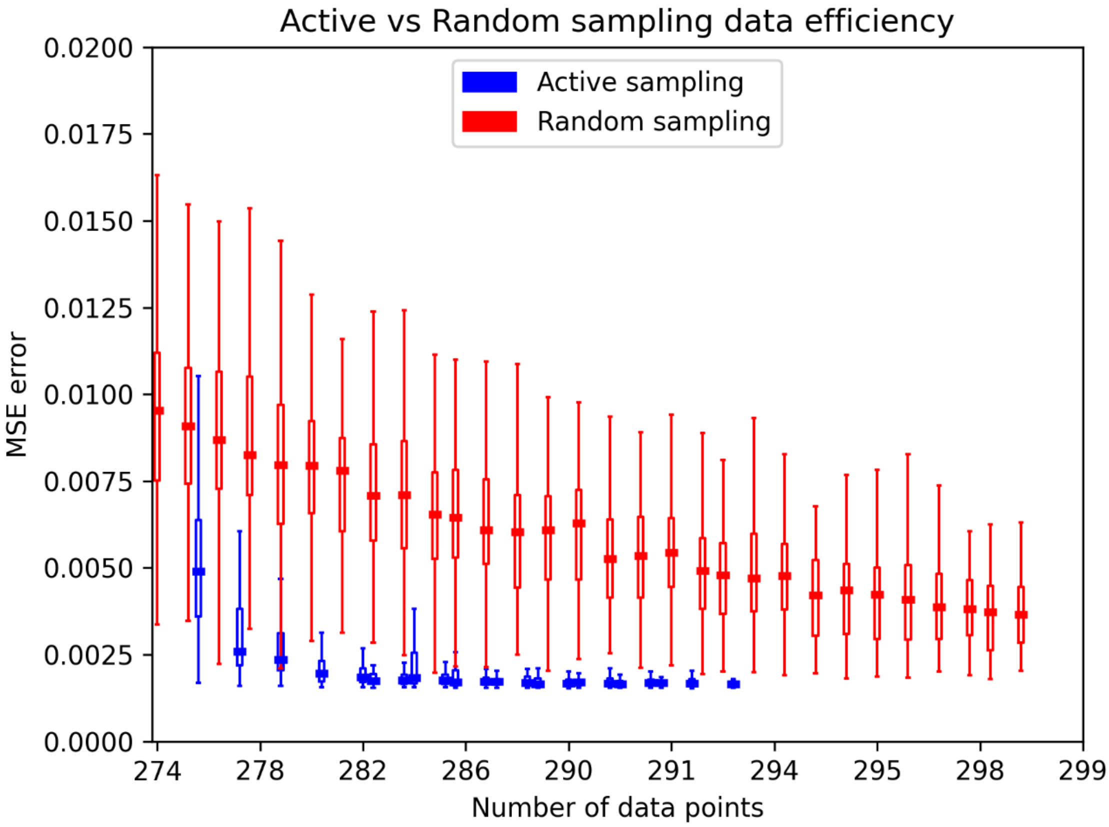


Figure 11 The sampling experiment results comparing the cross-validation MSE show that active sampling converges to a low error quicker than random sampling.

As expected, active sampling leads to a sample-efficient design of experiments. The intelligent selection of the next experiment allows us to reduce the number of conducted experiments, consequently reducing the effort required from the experimentee. Beyond this immediate benefit, this approach also has implications for online design of experiments, making it an intriguing avenue for further exploration.

3.6.4 Online design of experiments

While previous studies have recognized the increased scalability of VR experimental frameworks, this benefit becomes limited without the integration of online Design of Experiments (DoE). By combining online DoE with VR's software-defined operating conditions and portability, we introduce a framework that enhances the scalability of experiments, facilitating mobile, concurrent, and remote experimentation.

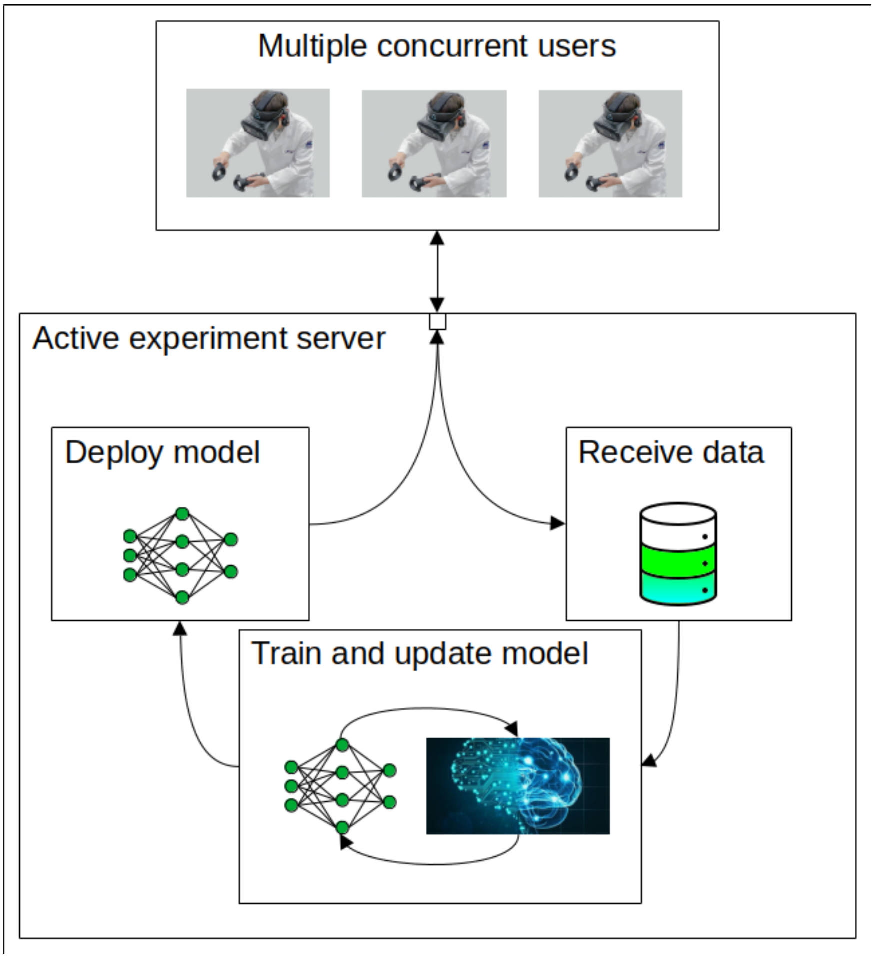


Figure 13 The proposed experimental framework improves the scalability of human experiments by combining online DoE, remote databases, reinforcement learning for deep mode architecture design, and on-device DoE capabilities.

This achievement is made possible through data storage on remote databases [59], on-device inference [140], online DoE as presented here, and model architecture search [119], [120]. Together, these tools enable the deployment of experimentation as a VR app, enabling remote-concurrent simulations, removing the need for experimental supervision, and enabling the model to adapt to significant changes in data. As a result, the scale offered by this experimental framework makes HITL simulations practical for previously challenging problems. For instance, methods that rely on large datasets, such as deep learning, were previously deemed impractical for modeling human behavior, but this technology has the potential to revolutionize such applications.

Moreover, this work highlights VR's suitability for investigating the intersection between human, data acquisition, and machine learning applications. VR provides an adaptable virtual environment capable of precisely measuring and simulating human interaction in a safe manner, which holds considerable promise for the development of human-centric applications.

3.7 Conclusion

The purpose of this study was to develop a VR experimental framework aimed at efficiently modeling manual assembly task duration. Through virtual assembly simulations of four dissimilar assembly tasks, we observed consistent behavior, which bolstered confidence in using

VR for human modeling. This suggests that employing virtual prototyping of HITL simulations can effectively reduce investment risk by deferring hardware investments while providing valuable performance data.

The framework utilizes a deep active learning model with online design of experiments (DoE) to achieve sample-efficient modeling. However, it's important to note that active learning requires prior knowledge or data of the process and may need customization of the acquisition function to address non-constant noise and avoid unnecessary sampling. By incorporating online-DoE, we overcome limitations of previous experimental frameworks, enabling scalability through remote, concurrent, and automated VR experiments, leading to larger and more informative datasets.

The resulting framework has great potential to include humans in modern manufacturing systems by reducing investment risk, automating the experimentation process, and facilitating the adoption of data-based human operator systems. Furthermore, its applications extend beyond manufacturing, warranting exploration in fields like healthcare and military training. The versatility of this VR interface in prototyping the intersection between human and machine learning systems presents exciting opportunities for researchers and practitioners alike.

In conclusion, this VR experimental framework offers a cost-effective means of HITL simulation with far-reaching impacts across various domains.

4. A decision framework based on human assembly and additive manufacturing

4.1 Abstract

There is a combinatorial explosion of alternative variants of an assembly design due to the design freedom provided by additive manufacturing (AM). This work presents a novel virtual reality-based decision-support framework for extracting the superior assembly design to be fabricated using the AM route. It specifically addresses the intersection between design for manual assembly and design for additive manufacturing using axiomatic design theory. Several virtual reality experiments were carried out to achieve this with human subjects assembling parts.

Firstly, a simplified 2D table assembly confirms the independence of assembly time and assembly displacement error. Then, an industrial lifeboat hook with three assembly design variations is assembled to evaluate the possible combinations. The technique effectively identifies the assembly design most likely to meet the requirements. This novel technique can incorporate human assembly with existing virtual prototyping methods and will reduce the number of prints while improving the final product's quality.

Finally, a graphical user interface illustrates the potential of the decision framework to enable manufacturers to choose the best assembly design.

4.2 Introduction

4.2.1 Background

The introduction of three-dimensional (3D) printing in assembly design necessitates the ability to determine the best assembly design, especially during the early design phases when various alternatives arise due to part consolidation (PC). Part consolidation, an aspect of design for additive manufacturing (DfAM), involves combining parts to reduce the total count in an assembly [141]. Various techniques, both conceptual [142], [143] and numerical [144], [145], address PC. For instance, [146] proposed a numerical approach for selecting part candidates for 3D printing in specific assemblies, and [147] presented a conceptually oriented PC approach for a single-component assembly printed using laser powder bed fusion, resulting in enhanced performance.

Moreover, early in the design process, a customer dealing with a multi-component assembly desires an assembly design that caters to human-centric design aspects. Human-centric design accounts for how humans interact with design artifacts [148]. In this context, design artifacts refer to the parts of assemblies to be fabricated using additive manufacturing (AM). Two key questions emerge: (1) How can human-centered design aspects be effectively integrated, and (2) How can conceptual and theoretical approaches be combined to select the optimal assembly design?

Virtual reality technology holds significant promise in addressing these questions. Virtual prototyping plays a pivotal role in enhancing product quality and facilitating a continuous improvement process. While the concept of using VR for assembly isn't groundbreaking, as noted by [149], the recent affordability and widespread availability of VR headsets have sparked a surge in its popularity. This trend is evident in the adoption of VR applications in construction, safety training, and emergency evacuation simulations [56], [57], [150], though it's worth noting that there's room for further development in blue-collar worker training.

In a study conducted by [106], it was discovered that VR positively impacts final product quality and expedites time-to-market across various domains, including manufacturing, training, and design. Additionally, VR serves as an effective tool for employee assembly training, as observed by [62], [63]. This multifaceted use of VR has the potential to address challenges in additive manufacturing (AM) design, thus preempting printing-related hurdles.

Virtual reality has gained recognition as a valuable tool for human involvement in experimental research [59]. To aid in the selection of optimal assembly designs, the well-established axiomatic design (AD) theory is used [151].

4.2.2 Motivation

This study seeks to leverage VR and AD applications to incorporate human aspects into the selection of the best assembly design for DfAM. Abidi et al.'s study [63] demonstrates that participants receiving VR training exhibited improved performance, as evidenced by fewer errors and reduced assembly time compared to traditional training. As for AD, it has been widely applied across various sectors for nearly three decades, including software [152], manufacturing systems [24], decision-making [153], and other domains [154]. AD serves as the scientific foundation, with its developed axioms [155]: independence (AD-1) and information axioms (AD-2). AD-1 insists on establishing independence between functional requirements (FRs) and design parameters (DPs). AD-2 serves as a filter for designs already complying with AD-1.

4.2.3 Objectives

The study aims to merge VR and AD for enhancing the selection of the best assembly design in the context of DfAM, accounting for human-centric design considerations. It seeks to provide a structured framework for this purpose, offering the potential for improved assembly design selection.

4.2.4 Contents

To achieve the objectives outlined above, the study follows a comprehensive decision framework. This framework involves:

1. Defining customer needs (CNs) and mapping them to requirements, incorporating DfAM-specific constraints.
2. Verifying the design matrix for independence using VR experiments as per AD-1.
3. Data processing based on digital twins for applicability in AD-2.
4. Selecting an assembly design that likely satisfies the design range (DR) in terms of probability density.

The study's novelties include incorporating human aspects through assembly time and assembly displacement error within DfAM constraints and focusing on filtering the best assembly design rather than identifying the best part candidates for PC.

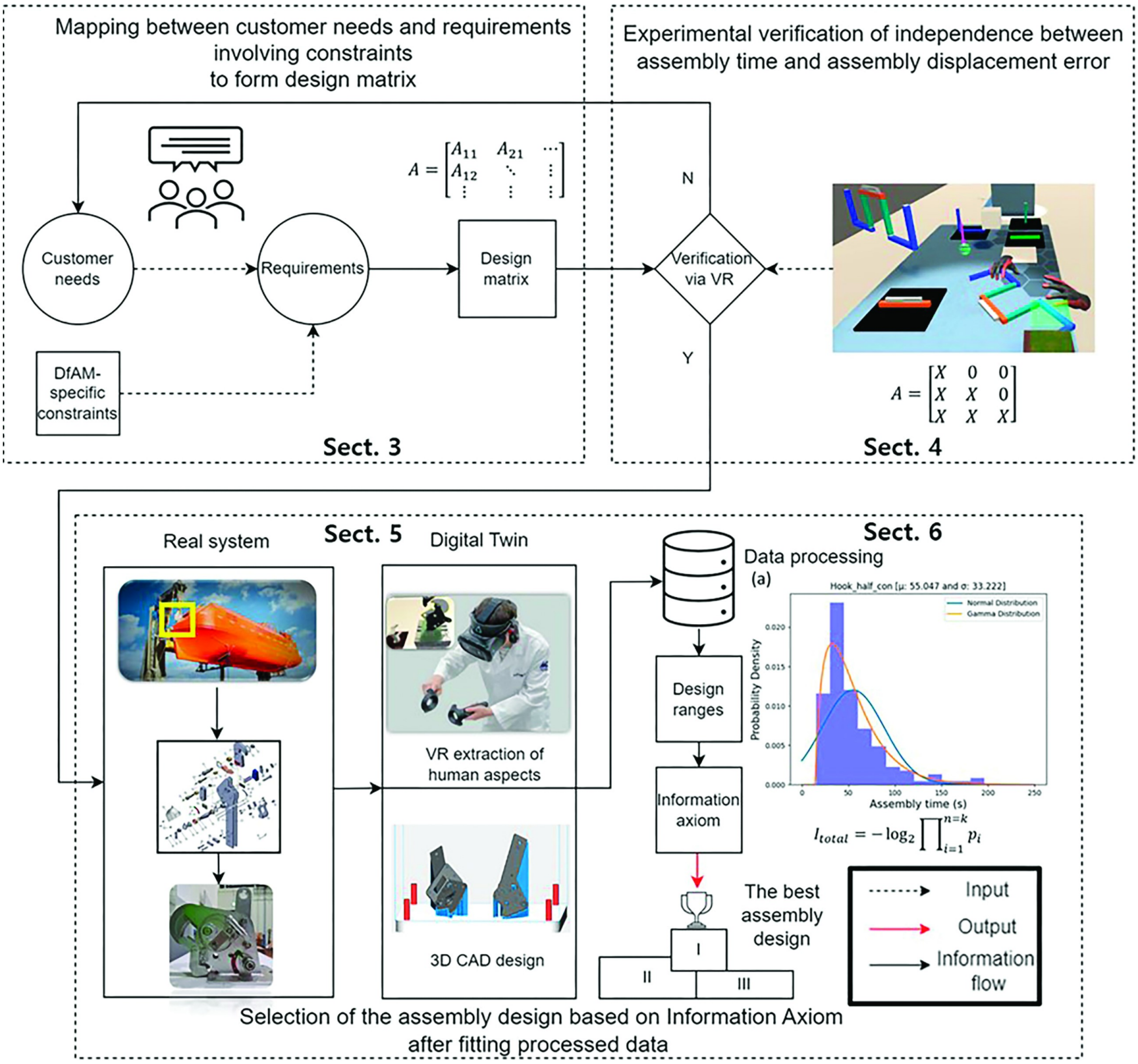


Figure 10: Overview of the proposed decision framework. A real system refers to a case study. Input, output, and information flows are indicated accordingly.

4.2.5 Contents Overview

The paper's organization is as follows:

- Section 2 provides a background on AD and its applications in AM and DfAM.
- Section 3 presents the newly proposed DfAM decision framework.
- Section 4 details the experimental design for extracting the human aspect of design and verifying AD-1 using a design matrix involving human subjects.
- Section 5 offers a case study of a lifeboat hook assembly to demonstrate the decision-making framework.
- Section 6 reports the results and discusses the selection of a superior assembly design.

4.3 Literature Review

In the early design stage of assembly, several approaches have been proposed to guide the process. These include DfAM-based guidelines [156], TRIZ [157], AD [158], machine learning-integrated DfAM [159] and the integration of these methods [160], [161]. Among these, AD has garnered significant attention due to its structured and systematic design solutions. Developed by [155], AD offers a theoretical framework for effective design. According to [162], design involves four domains: customer, functional, physical, and process. These domains interact, with AD providing a standardized thinking process for this interaction.

The "customer domain" defines what a customer seeks in a product. These customer needs (CNs) are mapped to the "functional domain," where functional requirements (FRs) and constraints are defined. The "physical domain" generates design parameters (DPs) to meet the specified FRs and constraints. The "process domain" defines processes to satisfy FRs using process variables (PVs).

AD facilitates decision-making by ensuring it doesn't violate two core axioms. The first is the independence axiom (AD-1), stating that FRs should be independent of each other and show’s up as a triangular design matrix [A]. The second information axiom (AD-2) quantitatively defines the best design satisfying AD-1 using the information content.

4.3.1 Applications of AD in AM and DfAM

AD has found applications in AM and DfAM. Some notable uses include optimizing 3D printing technology selection, guiding DfAM strategies [158] , and identifying critical DfAM and design for environment guidelines [163]. AD has also been applied in understanding the design freedom and limitations of AM [164] and redesigning components for improved performance [165, p. 20].

However, there's a gap in the literature concerning the use of AD-1 within DfAM frameworks to create a design matrix through VR and to numerically capture human aspects related to the interaction between human subjects and design artifacts.

Table 1: Summary of studies using AD for AM, illustrating this study is the first to verify AD-1 and include human assembly performance

AD works in DfAM	Opportunistic	Restrictive	Verification of AD-1	Human aspects of design
Salonitis (2016) [158]	x	o	x	x
Renjith *et al*. (2020) [165]	o	o	x	x
Toguem *et al*. (2020) [166]	x	o	x	x
Chekurov *et al*. (2019) [164]	o	o	x	x
Boca *et al*. (2021) [167]	x	o	x	x
Agrawal (2022) [163]	o	o	x	x
This study	o	o	o	o

To address these issues, a new assembly-level design framework was proposed. This framework considers DfAM-specific constraints and human aspects based on AD, enabling the production of assembly parts through compatible AM processes. It also introduces a graphical user interface to enhance practicality.

4.4 Novel DfAM Decision Framework Based on AD

In this section, we explain how the AD-adopted DfAM decision framework was developed with a focus on the inclusion of human assembly processes. The previous lack of human aspects of design in AD-based DfAM frameworks will be addressed by offering experimental design factors and data-driven distributions. Before that, domain-specific definitions are clarified.

In practice, many stakeholders provide design requirements in product design phases. One such requirement is from the perspective of the end-users, wherein FRs are considered as the primary factor, while the second requirement is from the perspective of the assembly or manufacturing process, which conveys information through so-called nFRs [168]. Thompson [168] was the first to mention nFRs, emphasizing that they should be explicitly identified to comply with a manufacturing point of view. In this regard, our new approach constitutes the extraction of nFRs instead of FRs; however, mathematically, FRs and nFRs serve a similar role in both axioms. Furthermore, they can be regarded within the same functional or requirement domain, as reported by [169]. Characterizing key CNs during the design process ensures that no significant components of the problem are overlooked. Herein, CNs are referred to as manufacturing process needs (MNs)[170]. Nevertheless, for the selection of assemblies, we assume that FRs are already satisfied; hence the main emphasis is on nFRs.

4.4.1 Human involvement in the design process: assembly time and assembly displacement error

In this study, nFRs were extracted from MNs to enhance assembly and AM productivity separately, unlike in [170] work. The number of parts and fasteners, handling, and insertion issues are considered in terms of DfA to evaluate assembly complexity [171]. This study focuses on manual assembly to both enhance assembly productivity in low-volume manufacturing and to demonstrate the human aspect of assembly designs.

In the first stage of the proposed approach to improve DfA productivity, assembly time (nFR1) and assembly displacement error (nFR2) should be verified for their independence. Additionally, the support volume (nFR3) of different assembly designs of a real case study under DfAM constraints is considered to enhance AM productivity. After the identification of nFRs, DPs are also obtained, as demonstrated in the coming sections. Next, the motivation behind providing the above-mentioned nFRs is explained in brief.

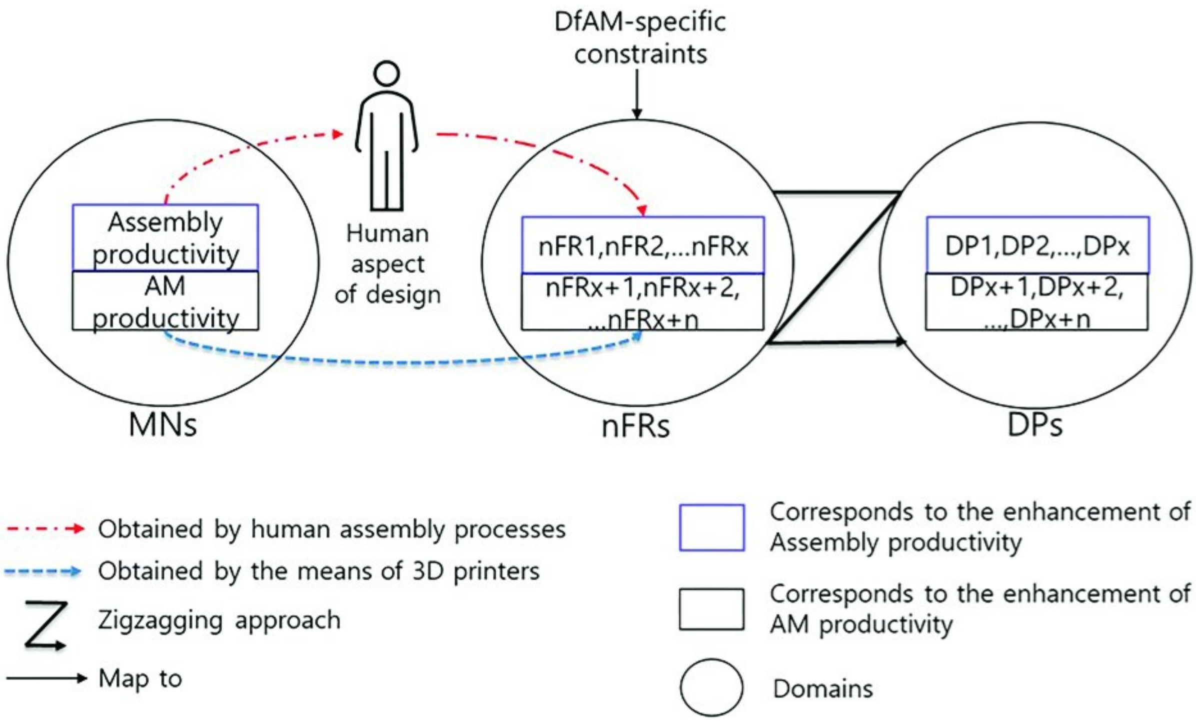


Figure 11: Enhancement of assembly and AM productivities via human involvement mapped to non-FRs. PVs are not shown here as process parameters are assumed to be fixed

nFR1 – assembly time: It is a critical factor in supply chain that governs a major portion of the manufacturing costs. Reducing assembly time of a product by 50%–75% via the implementation of the DfA rules results in a financial gain for industry sectors [12].

nFR2 – assembly displacement error: It is a crucial metric for evaluating different combinations of PC assemblies. In this study, this is used

- to assess the design complexity qualitatively;
- to quantify assembling error during manual assembly;
- to offer an assembly line worker a controlled environment; and
- to offer ways of interaction between people and the assemblies before the launch of the product to accelerate the learning process of assembling.

nFR3 – support volume: Before 3D printing, build orientations of the parts in the assembly must be properly managed. Owing to the large projected area, the support volume increases as the number of parts consolidated increases [145, p. 202]. This subsequently renders the removal of the support parts even more difficult [172].

To reiterate, nFR1 and nFR2 directly pertain to the human aspect of assembly designs because, in DfA, humans are extensively involved within manual assembly.

However, it should be demonstrated that nFRs are in the same highest level hierarchy before determining their DRs. This issue is associated with the construction and verification of the design matrix, which is primarily overlooked. For example, one may regard that as nFR1 increases, nFR2 reduces, implying that they are dependent and mutually inclusive. However, this may not necessarily be true. To avoid this, an experiment comprising four different 2D tables was performed to validate independence . Before, the DfAM-specific constraints must be clarified within the decision framework.

4.4.2 DfAM-specific constraints and study assumptions

In this study, we incorporate Non-Functional Requirements, specifically assembly time (formerly nFR1) and assembly displacement (formerly nFR2), within the functional domain. Alongside these nFRs, certain constraints are in place to define acceptable designs. It is important to note that these constraints are not expected to be entirely independent, and as such, the need to demonstrate their mutual independence is not necessary.

The primary constraint we address is the consistent maintenance of assembly build time and build cost while considering various assembly alternatives. This constraint is crucial because our focus revolves around the human aspects of assembly. This assumption remains valid due to the well-established correlation between the number of consolidated parts and increased support volume, ultimately impacting assembly costs, as previously discussed by [145]. Conversely, a high number of unconsolidated parts can significantly elevate assembly time costs, particularly in the context of the metal Laser Powder Bed Fusion (L-PBF) system. Therefore, based on these two distinct scenarios, we assume that the outcomes regarding build time and cost remain identical.

Furthermore, these constraints are directly influenced by the build orientations of assembly parts. Thus, we control the build orientations to minimize the need for support structures. Additionally, post-processing considerations are essential to ensure the removability of supports. Moreover, when assembly requires joining parts, welding costs come into play. However, for the purpose of this study, we assume that these welding costs are considerably lower than the 3D printing expenses, and therefore, they are disregarded, following the findings of [173].

Regarding assembly displacement, we make the assumption that components such as bolts with nuts, typically used for insertion, are not considered. This is because they do not contribute to assembly displacement errors, and our primary goal is to demonstrate the assembler's interaction with a specific design.

4.4.3 Data acquisition to select the superior design

One of the insights of this work is the acquisition of data from digital prototypes. Specifically, the assembly time and assembly displacement error (human assembly data) were gathered from a VR simulation and support volume (manufacturing) data from third-party software.

Primarily, digital twins have been utilized for various tasks in the literature, including optimization, security improvement, monitoring, predicting, user training, and enhancing a physical prototype or a process [174], [175]. Through VR technology, it is possible to interact between a virtual and real environment. For instance, data can be gathered from digital twins using VR's controllers in a real-time setting. After confirmation of design matrix satisfaction by AD-1, one can proceed to populate digital twin data, which contain human aspects of design via VR experimentations and pre-processed 3D printing assembly design. These data are used in the decision framework to evaluate the best design.

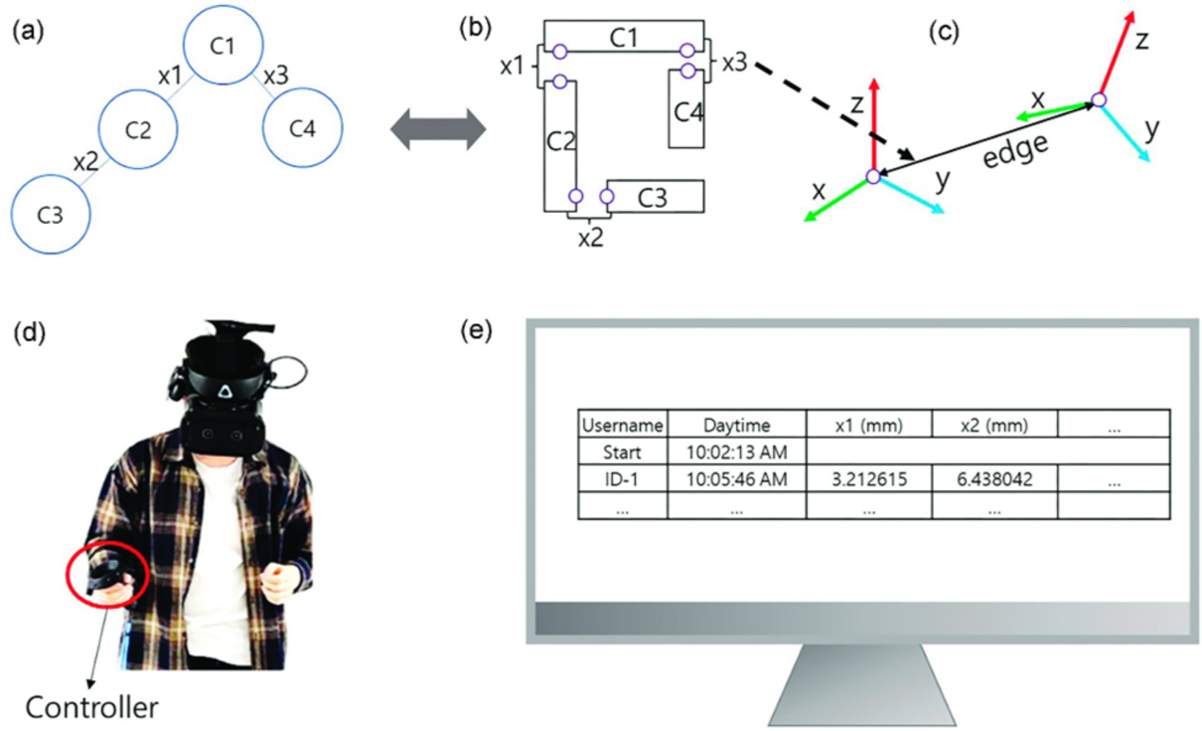


Figure 12: a) Assembly graph example for representative components, (b) representative components with edges and connectors, (c) general representation of the edges in 3D, (d) human subject with VR controller, and (e) assembly time and error recording as soon as connectors are joined.

4.4.3.1 Assembly time (nFR1)

To determine the assembly time in a VR scene, the starting time and submission time of each assembly were recorded. In addition, VR technology was used to create a simulated assembly environment closely resembling real-world conditions. Human subjects were able to accomplish the assembly tasks in a natural and intuitive manner as a result of the utterly immersive assembling experience. Thus, VR allows us to collect information on human subjects' movements and interactions with design artifacts which can help to quantify assembly time and displacement error in assembly procedures.

4.4.3.2 3.4.2. Assembly displacement error (nFR2)

The assembly displacement error, sometimes referred to as an error, represents the deviation of the assembled part from its reference position. It is calculated by summing the distances between the reference and actual locations of the parts. The error is calculated using an assembly graph depicted in the figure above. The unity module, which is easily reusable, is provided to facilitate this calculation. A brief explanation follows.

The graph's edges capture the distance between actual and reference assembly components, and it is summed to give the error of the assembly at hand. This graph consists of:

- **Components** which represent each part of the assembly.
- Each component has a few **connectors**. These are the points where components fit together. They resemble welding points.
- **Edges** capture the relationship between two connectors. Initially they contain the distances in meter Δx, Δy, and Δz
- Assembly displacement **error** is calculated by summing the radial distance of each edge. In this case, L1-norm was used as it places emphasis on the minor errors, where L2-norm would place more weight on larger errors.

3.4.3. Support volume (nFR3)

DfAM-specific constraints previously explained should be considered to extract support volume data. The data can be obtained by commercial pre-processing software such as Magics Materialise, for example.

To utilize obtained aforementioned nFRs data in information axiom, data processing needs then be carried out in terms of an appropriate distribution illustrated in Section S1 in the Supplementary file. In addition, DRs are used to define the allowable variations in the design without compromising the nFRs [170]. Thus, DRs are decided based on the nFRs subjectively because they demonstrate how well the design meets the targets while maintaining its independence.

This section shows how data acquired from digital prototypes were used to compare designs. Both third-party software for the support volume and VR to capture human assembly data were involved. Next, the details of the experimentation will be covered.

4.5 4. Experiment

4.5.1 Design of experiments

It is worth reiterating that using VR enables the evaluation of the human aspect of design by allowing for interaction with the design beforehand. VR scenes were programmed in such a way that they allow extraction of the activities of human subjects and record the corresponding data (nFR1 and nFR2) in real-time. The process was initiated using simple assemblies from the 2D table and subsequently progressed to utilizing actual assembly parts

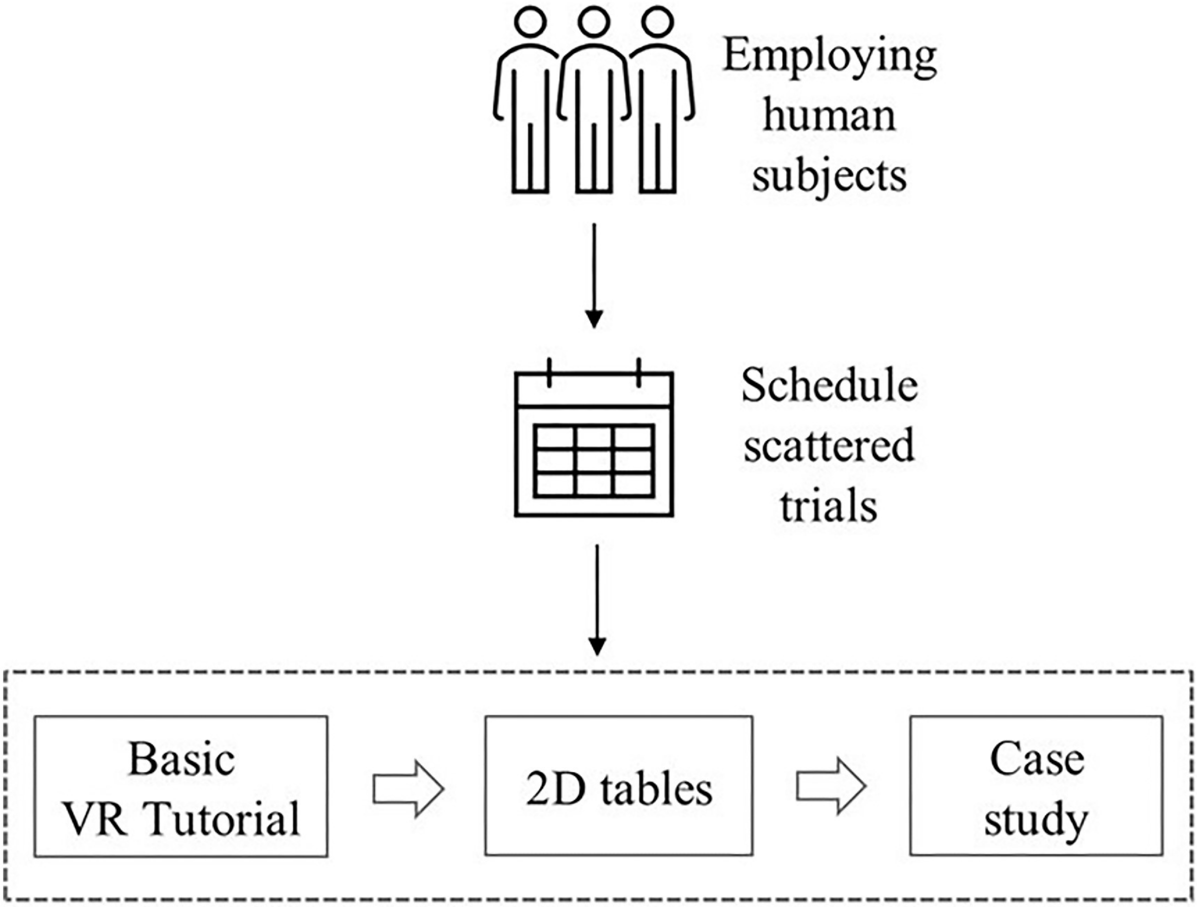


Figure 13: Outline of the design of experiments to obtain the human aspect of design (the dashed box represents the set of experiments). Basic VR tutorial and 2D tables are utilized to form the design matrix. Then, one can try to assess target assembly designs. In this study, the authors chose lifeboat hook assemblies described in Section 7.

4.5.2 Description of assembly operations

Human subjects were expected to assemble the components at the designated areas of each part. They received audio and visual feedback when they finished the task correctly. Initially, human subjects completed a tutorial to familiarize themselves with VR, the process, and the objectives. Then, the primary experimental tasks were conducted several times to facilitate and evaluate the learning process. As it pertains to assembling, the human subjects performed PC by joining the assembly parts.

4.5.3 Experimental procedure

VR experiments with 10 human subjects were conducted to establish this approach. The subjects are all male, with ages ranging from 18 to 29 years. The participants have little to no prior experience with VR. Throughout the 10 days of the experiment (two groups of five participants each performing across 2 weeks × 5 days), all participants tested in the morning and afternoon within non-repeating time slots.

In our study, there are three virtual scenes: (i) tutorial, (ii) 2D tables, and (iii) real assemblies. For each assembly task, all participants were shown video instructions and were well compensated for the experiments. In the beginning, all participants passed the tutorial scene and proceeded to the stage with 2D tables. There are four assemblies differing in the number of components, connectors, and edges. Each assembly was tested thrice on the first day, and then it was increased by one each day. The primary reason for the observed efficiency in assembly time is due to Wright learning, in which human subjects start to learn to assemble faster [30]. This learning process provides more assembly trials within 5 days. Similarly, in the second scene, the case study of the lifeboat hook was tested, and it followed the same procedure as the scene with the 2D tables.

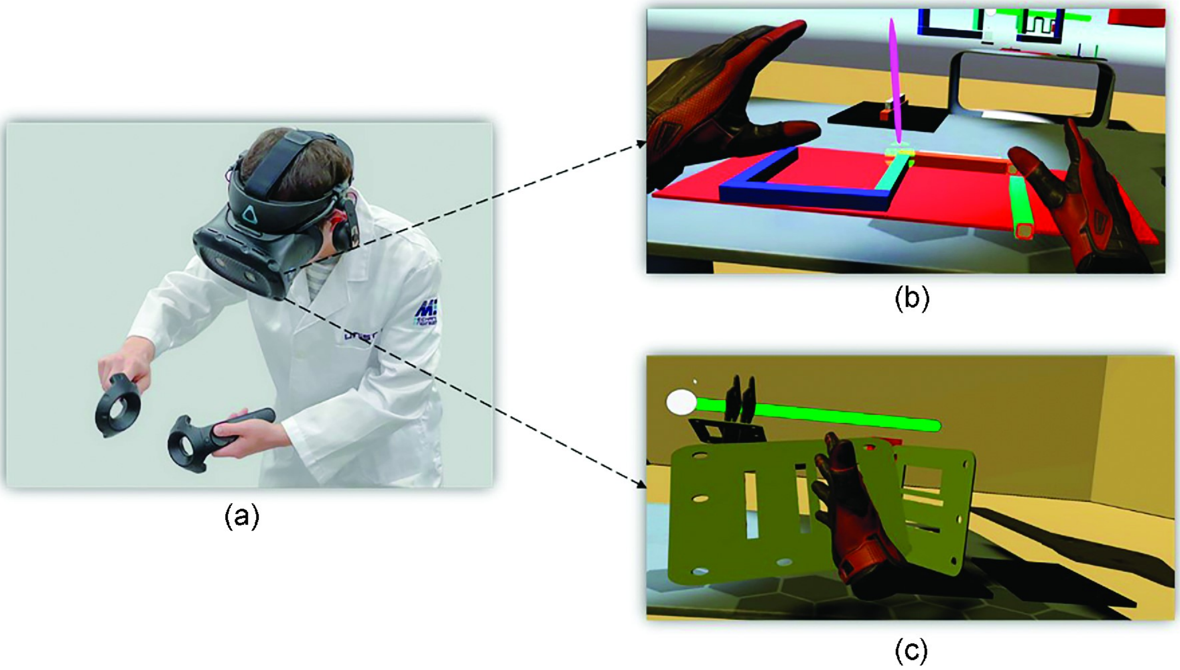


Figure 14: (a) Illustration of how a human subject experiments with assembly parts, (b) 2D table scene, and (c) Hook assembly scene.

As mentioned previously, the 2D tables are used to evaluate the orthogonality of nFR1 and nFR2, which pertain to enhancing DfA productivity. Different numbers of components, connectors, and edges are used to establish this independence. For example, as shown in the figure above and table that follows, the pairs of (T1, T3) and (T2, T4) are structurally and functionally the same but have different numbers of components. They were intentionally designed to observe the dependence between nFR1 and nFR2. Additionally, these 2D tables and respective numbers of components are chosen to test repeatability and to ensure ease in assembling for the participants. The 2D tables are expected to be assembled on the desk to avoid errors in 3D as if the parts are assembled using jigs and/or holders.

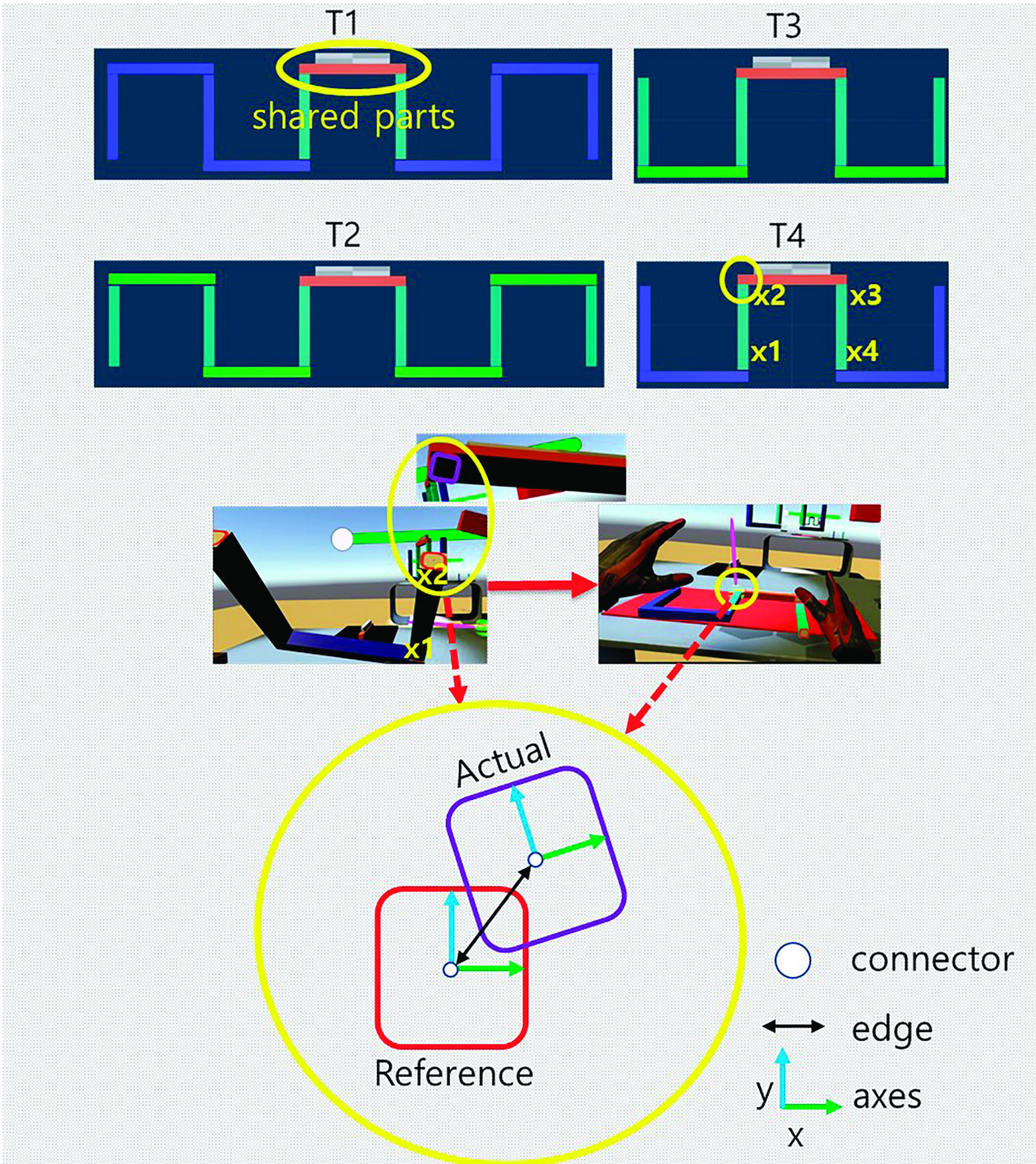


Figure 15: 2D tables with different numbers of components. Shared gray and red parts represent the upper side of all 2D tables. The different colored parts are distinguished by the edges. An example of the edges in T4 are highlighted as x1–4.

4.5.4 Verification of independence among nFRs

AD approach consists of several steps to ensure that all MNs are met systematically. The initial step in this study was to obtain a clear understanding of the MNs, with a particular emphasis on improving DfA and DfAM productivities to establish a desired design matrix. Once MNs are determined, the next step is to map them into the functional domain to identify nFRs. These nFRs are then decomposed into lower level nFRs until the lowest level of detail is reached. After analyzing nFRs, DPs, which are the design variables that can be adjusted to achieve the desired nFRs, are identified.

As mentioned earlier, DfA involves part handling and insertion times; thus, nFR1 can be decomposed into part handling time (nFR11) and insertion time (nFR12). The corresponding DPs are the number of parts (DP11) and the number of interfaces (DP12). nFR11 and DP12 are orthogonal according to [170] hence AD-1 can be satisfied. Orthogonality implies direct independence among either FRs or nFRs. In the case of nFR2, it can be further divided into human fatigue level (nFR21) and DfA complexity (nFR22) as well as respective DPs such as daytime (DP21) and the number of human subjects (DP22). This is explained by the inclusion of the scattered schedule during the experimentation to avoid human fatigue. It is accepted that humans perform better in the mornings [176]; hence, these DPs are critical when nFR2 is considered. Additionally, the nFR21 is not related to DP22; thus, this is the lowest level of detail for nFR2.

After a series of experiments with 2D tables, one can find a correlation between nFR1 and nFR2. It should be noted that the correlation coefficient was found between each edge of nFR2 and nFR1, also between the L1 norm of nFR2 and nFR1 to observe the independence wholly. The table that follows shows that $\max(|r|) = 0.11742$ implying a very weak correlation which can represent the independence of L1 norms of nFR1 and nFR2.

Table 2: Results show weak correlation (|r|<0.199) between assembly time and displacement.

2D tables	**Assembly displacement errors (nFR2)**										**L1-norm of nFR2 versus nFR1**
Assembly time (nFR1)	**x1**	**x2**	**x3**	**x4**	**x5**	**x6**	**x7**	**x8**	**x9**	**x10**	
T-1	−0.191	−0.120	0.134	−0.131	−0.061	−0.219					−0.113
T-2	−0.101	−0.143	−0.159	−0.0797	−0.016	−0.004	0.010	0.008	0.061	−0.067	−0.042
T-3	−0.149	−0.106	−0.2235	−0.075	−0.034	0.014					**−0.117**
T-4	−0.0957	−0.137	−0.075	−0.0398							−0.109

4.6 Case Study – Lifeboat Hook Assembly

The proposed decision framework is illustrated by involving the Hyundai lifeboat hook assembly from the previous study, along with different versions of the PC-ed assemblies [172]. The hook assembly is an excellent example for demonstrating PC owing to its numerous parts.

Combinatorically, w30 hook assembly designs can be determined owing to the layout of the parts. Nevertheless, as it is impractical to include all of them, some constraints should be set. In the proposed approach, the DfAM-specific constraint is to maintain the build time and costs of all hook assembly alternatives the same. To do that, one must orient all the parts (excluding the auxiliary and miscellaneous components such as fasteners, nuts, and covers) to have a minimum support volume. However, the support volume of each design varies among assembly designs owing to the number of consolidated parts; hence it can be used within the intended design matrix.

After applying the constraints, only three assemblies are selected to demonstrate the importance of human aspects in the design, as shown in the figure below. These three assemblies vary in terms of the primary plates that constitute a substantial portion of support volume (c). The other parts are the same in all assemblies; thus, only these large plates will be used to evaluate nFRs. . Furthermore, (d) shows edges during the assembly process, while (e) shows the exaggerated one.

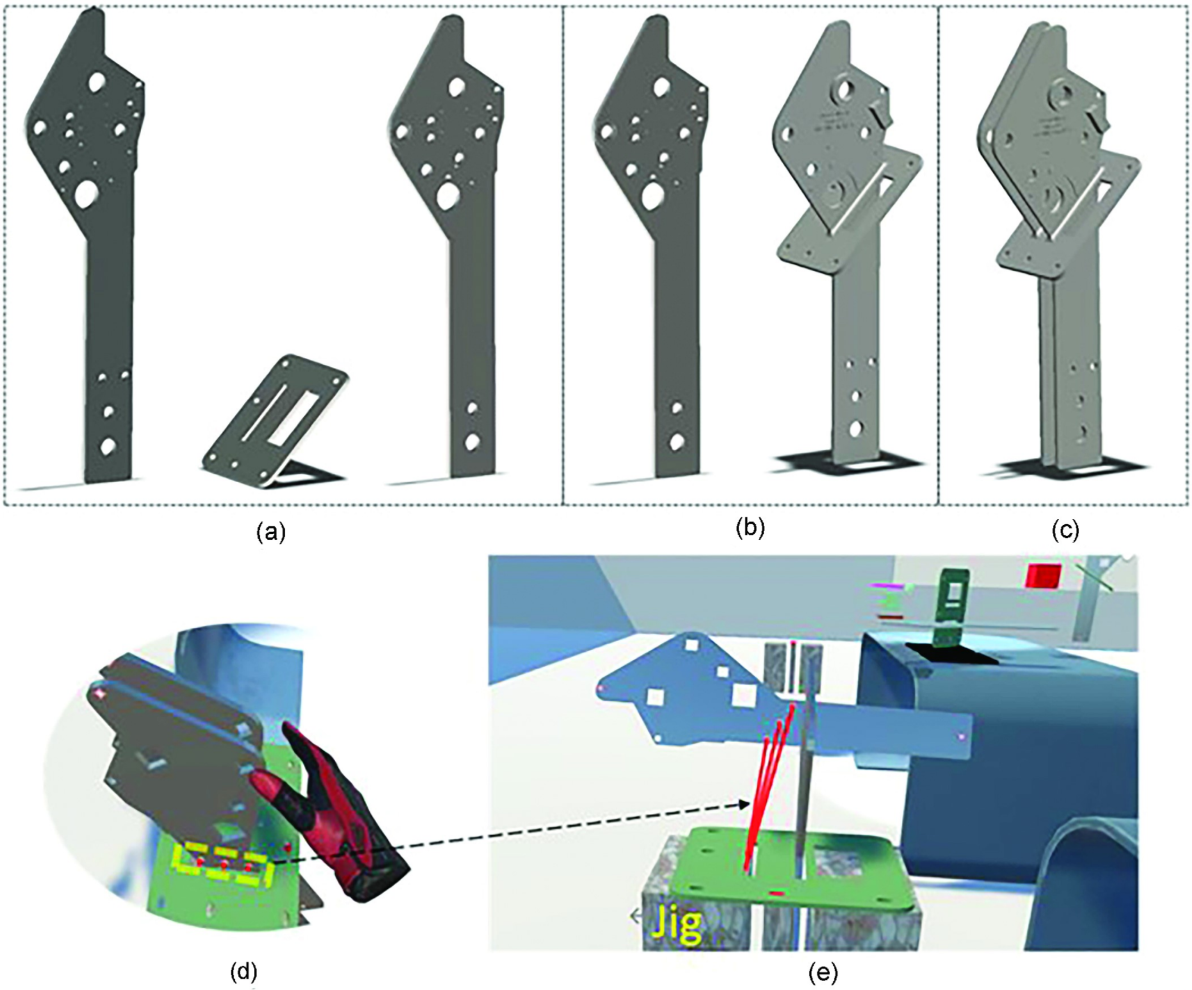


Figure 16: Hook assemblies. (a) unconsolidated, (b) half-consolidated, and (c) consolidated. Unconsolidated and half-consolidated ones are assembled using jig in VR environment to control misalignment in 3D. (d) Edges of the assembly. (e) Exaggerated edges for visual illustration.

For nFR1 and nFR2, a true scale of the hook parts in VR is employed. Nevertheless, nFR3 possesses values of downscaled (by 1/3) alternatives, as one must fit the hook assembly within the L-PBF printer to demonstrate fabricability. To re-emphasize, instead of CNs, MNs are considered because the original design and consolidated variations of hook assembly are already functionally valid.

4.7 Results and Discussion

The experimental data were processed using an in-house python script before it could be evaluated using the framework. When AD-2 is involved, it is customary to use a normal distribution [177], albeit this may not meet the demands of this study given that its values might reach negative infinity. The most appropriate distributions were selected and fitted for each system range of nFRs. For example, the system range of nFR1 can be interpreted as a gamma distribution as shown in the figure that follows.

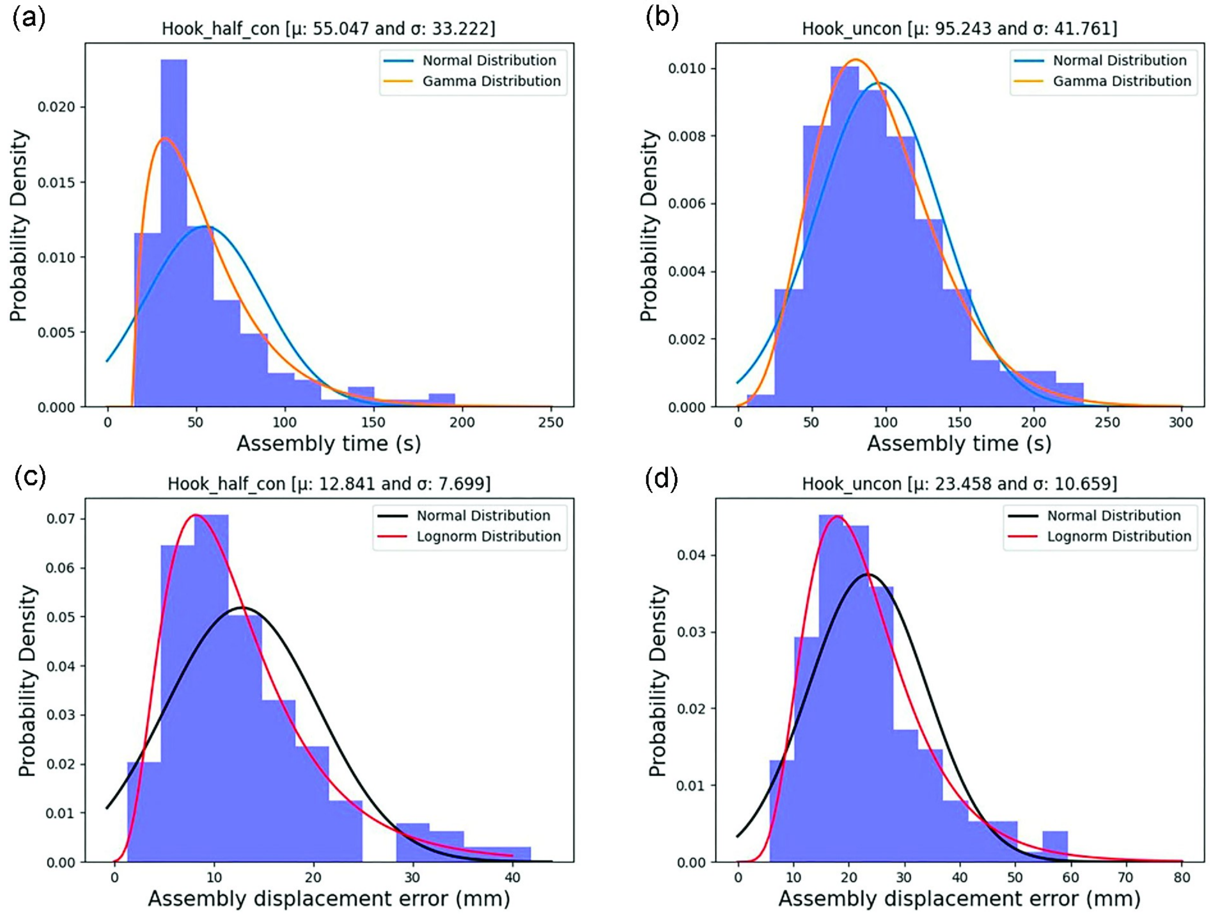


Figure 17: Representative fitted data of nFR1 and nFR2 with means (μ) and standard deviations (σ) of half-consolidated hook designs [(a) and (c)] and unconsolidated hook designs [(b) and (d)].

Normal distributions would not represent a real scenario as nFR1 > 0 and nFR2 > 0 because its random variables are the wait time until the n^{th} assembly was assembled. Whereas lognormal distribution is ideal for nFR2 that cannot take negative values especially when a dataset is skewed to the right, hence it was chosen to be the best fitting distribution as it is seen from the figure (c and d).

Nevertheless, in terms of the means, for unconsolidated hook assembly, it took 73.0% more time to assemble (more nFR1), while the half-consolidated design has less 82.6% assembly displacement error (nFR2) than that of the unconsolidated one. This reveals the significance of PC in reducing the assembly time and assembly displacement error pertaining to the human aspect of design. However, it should be noted that to choose the best assembly design, in further steps the support volume (nFR3) will be also taken into account, which is compensated by the number of parts consolidated.

Furthermore, Table S6-1 contains the fitting parameters such as shape, location, scale, and mode of nFR1 and nFR2 for reference. The goodness of fit of the gamma and lognormal distributions can be confirmed using the Kolmogorov–Smirnov test (kstest). The kstest showed the data fit the distributions sufficiently (i.e., P-values > 0.05), as in Table S6-2.

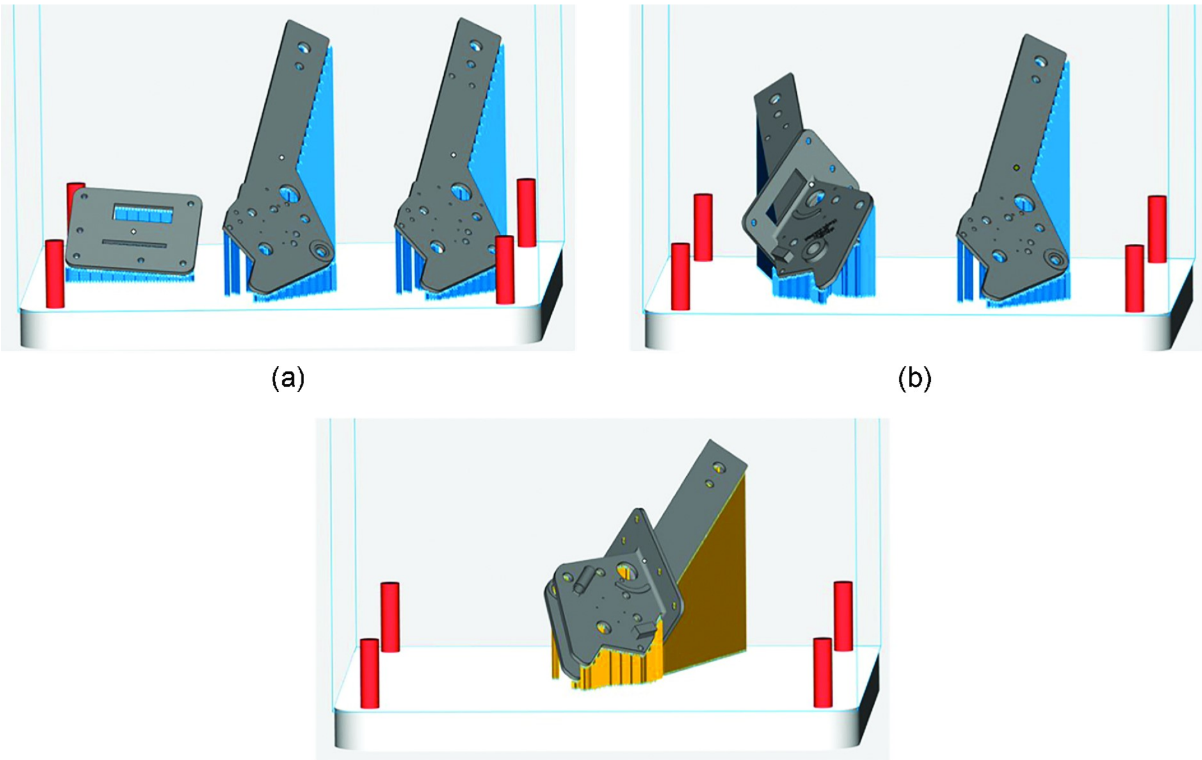
Once the data processing is complete, a designer can select DRs that satisfy the desired nFRs [178]. These DRs play a crucial role as they indicate the design's ability to accommodate variations in tolerance. The characteristic of AD theory, weighting factors are not needed as the tuning of the DRs already shows which nFR is more crucial [179]. In this regard, the DRs are chosen in three distinct levels—less, moderate, and more. Each level expresses the importance of the specific nFR, and the selection of the levels facilitates the matching of the capabilities of a machine shop to manufacture a particular assembly design. For example, if a customer wants their product to be assembled quickly, he chooses nFR1 as less and looks for machine shops that could satisfy the customer's need on time.

The table shows the DRs of nFRs along with the corresponding levels. They are chosen based on the conducted experiments (i.e., nFR1 and nFR2) and characteristics of hook types (i.e., nFR3).

Table 3: Design requirements for hook assembly

DRs	Less	Moderate	More
nFR1 (s)	20	55.561	75
nFR2 (mm)	2	13.33	24
nFR3 (mm^3)	10 000–23 000	10 000–33 000	10 000–43 000

Therefore, herein, moderate DRs are set to be the means of the modes of gamma and lognormal distributions, for nFR1 and nFR2, respectively. The modes are used because they are defined as the values appearing most frequently in a dataset. Thus, moderate DR of nFR1 is 0–55.561 s while that of nFR2 is 0–13.33 mm. DRs of less and more are set to demonstrate quantification at lower and larger values, respectively, which can also be tuned by a user based on the experimental results.



(a) (b)

(c)

Figure 18: The support types of (a) unconsolidated, (b) half-consolidated, and (c) consolidated assemblies are default block, lines and point supports generated automatically.

Further, the system ranges of nFR1 and nFR2 can be found experimentally, but in the case of nFR3, the system ranges for each assembly are set to be between the minimum and maximum values of the support volume identified by Magics (v.24.1). nFR3 can be regarded to be uniformly distributed because the continuous uniform distribution exhibits the same probability of an outcome over a DR. The DRs of nFR3 were selected according to the values of assembly types. The figure shows the support structures of three hook assemblies.

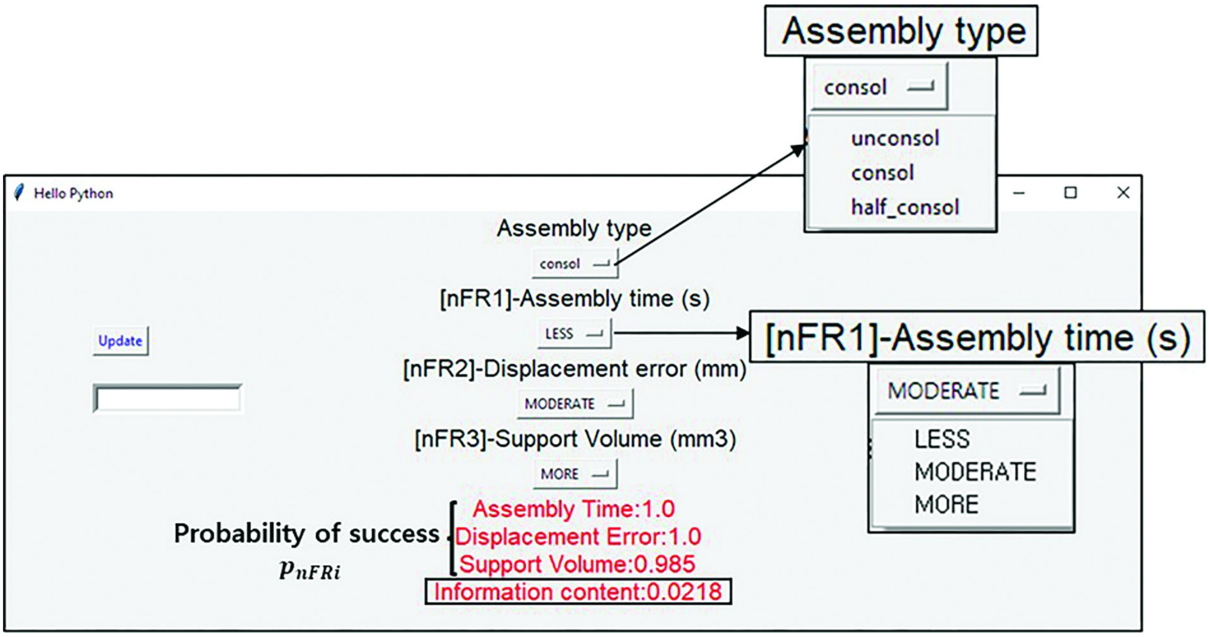


Figure 19: The in-house GUI to find the best assembly design based on AD-2. In this case, it is a consolidated type.

Calculating information content across the different DRs for various assemblies is a repetitive task and thus lends itself well to automation. For this reason, an in-house GUI for selecting the best assembly design has been developed. First, the assembly type should be chosen, following which corresponding nFRs with the desired level of DRs can be selected. Therefore, GUI calculates the probability densities of nFRs and the information content of that hook type, as shown in the figure that follows. At the same time, the probability densities of every hook type are plotted and calculated upon pressing “update” as shown in the next figure. Note that the GUI can be easily modified according to any assembly design; hence it is not limited to the hook assembly.

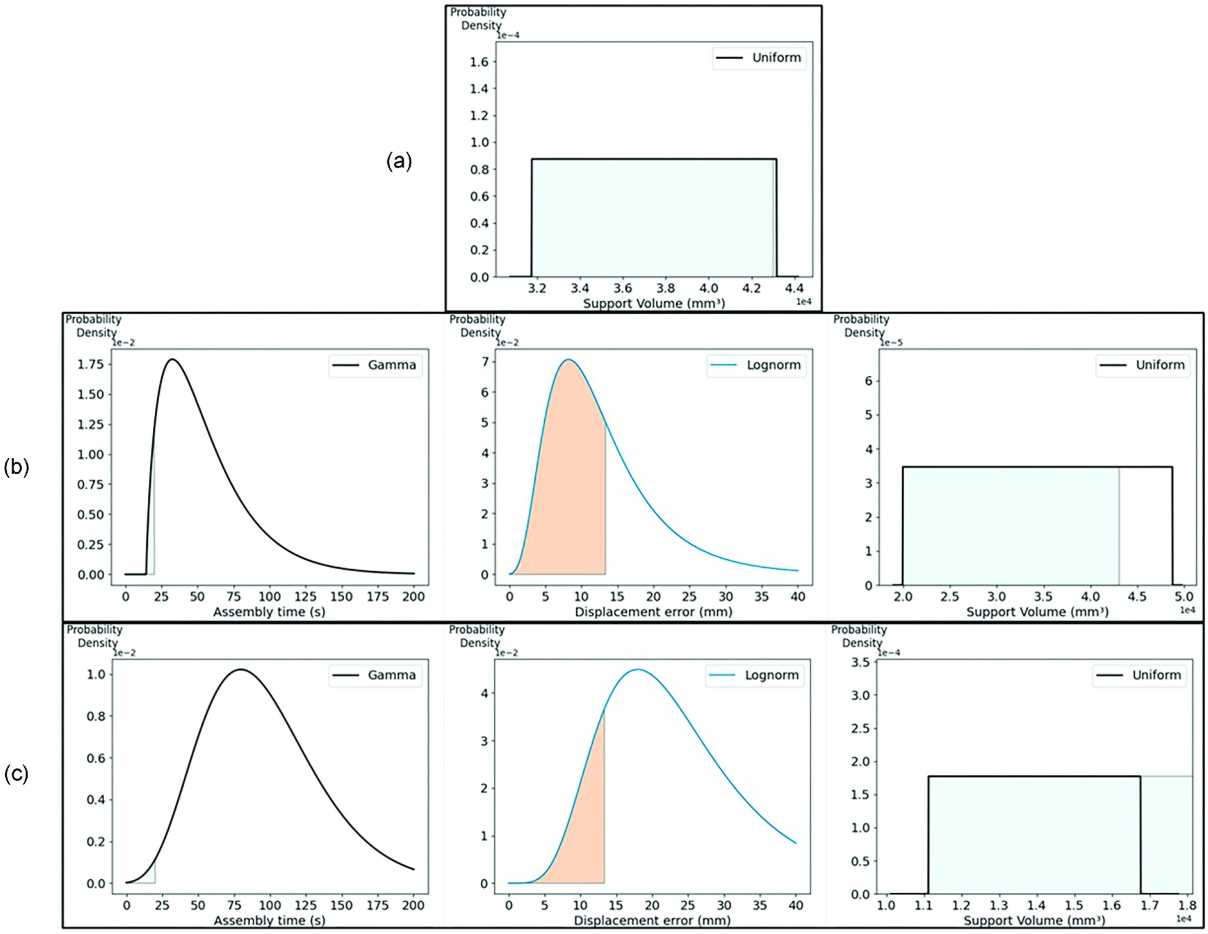


Figure 20: GUI that displays probability densities of (a) consolidated, (b) half-consolidated, and (c) unconsolidated hook assembly designs.

As a comparison, probability density plots and a summary of the table of information contents of each hook type are shown when DR{nFR1} = Less, DR{nFR2} = Moderate, and DR{nFR3} = More. Based on the information in AD-2, it can be concluded that the consolidated hook assembly is the best design in terms of information content, as demonstrated by the results, given the selected DRs. Additionally, the figure display the probability densities of half-consolidated and unconsolidated hook assemblies, respectively. Moreover, if one wants to utilize the framework for any other assemblies, one of the nFRs can be disabled. For example, for assemblies that require bolts, nuts, and riveting, nFR2 can be switched off, and the evaluation can be proceeded based on nFR1 and nFR3.

Table 4: A representative case of the probabilities of satisfying the requirements

	Unconsol	Half-consol	Consol
pnFR1	0.0078	0.0409	1
pnFR2	0.15	0.6257	1

p_{nFR3}	1.0	0.8001	0.985
I_{total}	9.7312	5.6104	0.0218

As can be observed, a new AD-based assembly-level DfAM framework enabled by VR led us to extract the human aspect of design, which has been presented for the first time to the best of the authors' knowledge. The applicability and versatility of both AD and VR ensure that human aspects can be numerically expressed, thus eliminating subjectivity in decision-making to a certain extent.

4.8 Conclusions and Future Works

This study presents a unique AM design decision framework incorporating DfA, DfAM, and AD theory to extract the most desirable assembly design in terms of probability density. The detailed workflow to improve assembly and AM productivity utilizing AD involves hitherto mostly disregarded human aspects of design at the early design stage. By assisting an assembly line worker with a VR environment in advance, nFRs can be quantified based on the interaction of human subjects with assembly design alternatives. The contribution of our proposed study is manifold and can be listed as follows:

- Provision of a structured and experimental base for verifying a design matrix for independence.
- Quantification of nFR1 and nFR2 within VR scenes.
- Demonstration of the framework on an industrial lifeboat hook assembly.
- Extraction of the most preferred assembly based on specified DRs.
- Automation of a resultant workflow via a newly developed GUI.

As was shown, PC can produce several different assembly types. Our study can assist in determining the ideal assembly design to be printed using, e.g., L-PBF printers. However, the authors do not consider various build orientations; hence, the parts' costs are assumed to be constant. In future work, cost constraints can be lifted to involve multiple build orientations rather than just minimizing nFR3. Furthermore, the DRs when applying AD-2 must be experimentally identified, which might require extensive resources. However, once extracted, DRs will be applicable for multiple assembly designs at the detailed design stage. Moreover, this study shows that including human assembly processes in an AD-based AM decision framework can be potentially used before 3D printing any assembly designs.

5. Digital mocking pattern for development of human-centric assembly systems

The recent onset of Industry 5.0 as techno-centric → human-centric transition. Design patterns are solutions to commonly occuring problems which can better equiped developers for this transition by providing structure to solution, modularly seperating components for resuse, providing a common vocabulary faciliating communication.

This work proposes applying the software mock pattern to development of human-centric systems. The pattern substitutes the digital twin for development of the system.

The pattern is retro-reflected in three previously published articles to illustrate its flexibility to several tasks. Illustrating its use in validating established models hold within a specific domain and investigating novel models, developing novel dynamic scheduling systems that are sample efficient, developing decision frameworks that utilize human performance data.

We find that this pattern can be applied to the case studies, illustrating its flexibility. Moreover, we suggest that it encourages creativity by combining component in a virtual prototyping environment that can be rapidly iterated on.

The cost of simulation and development for this method can be significant and design decision must be made on a percase bases to account for feasibility. On the other hand, this approach is flexible enough to be applied to domains were human-error risk is high like medical surgery, military application, long-distance driving, and mining.

5.1 Introduction

5.1.1 Background

5.1.2 Motivation

5.1.3 Objectives

5.2 Dynamic scheduling as human control

This chapter proposes as a state based model for dynamic scheduling as control of human system.

Naive scheduling typically only considered the systems performance. While scheduling for human well-being can consider the capabilities of humans and improve system performance, while personnel well-being through expanding scheduling to consider work-rest, job rotation, cross-training, and task learning-and-forgetting [66]. These mathematical models typically model the production performance in terms of task duration or throughput rate, human-error, etc []. Often dynamic scheduling models contain design variables are used to calibrate models learning rate, fatigue rate, etc. These represent the human internal state.

Evidence suggests these states interact. For example, fatigue based schedulers are simultaneously optimize throughput rate and increased probability of human error [31], [91].

Recall that control of humans is a sensitive topic. Chronically high fatigue levels are associated with worker health issues, human error, injury, and worker (dis)statisfaction [180]. This illustrates the implications of how human control hass additional constrains that ensure the well-being of the operator.

On the other hand negative perception of the topic affects the adoption of the technology. Hollywood franchises like Terminator and iRobot has raised popular concerns that “humans should control robots, not the other way around”.

We find when the objective (function) is empathetic, it AI control of humans may be permissible. For example, an objective function that reduces the number of experimental samples required to calibrate a HPM [60]

, in turn reducing the human effort required- an empathetic outcome. On the other hand, poor objective functions that consider only production outputs will likely maximize time on task, likely leading to high levels of fatigue and eventually health-issues or injury.

While there is limited evidance, in many cases better consideration of human states leads to better production outcomes. Fir example, low levels of fatigue are associated with low risk of injury and higher production quality. Similarly better congitive design leads to lower human error and higher worker statusfaction [cms-italy]. This suggests that “what is good for the operator is good for the production system”.

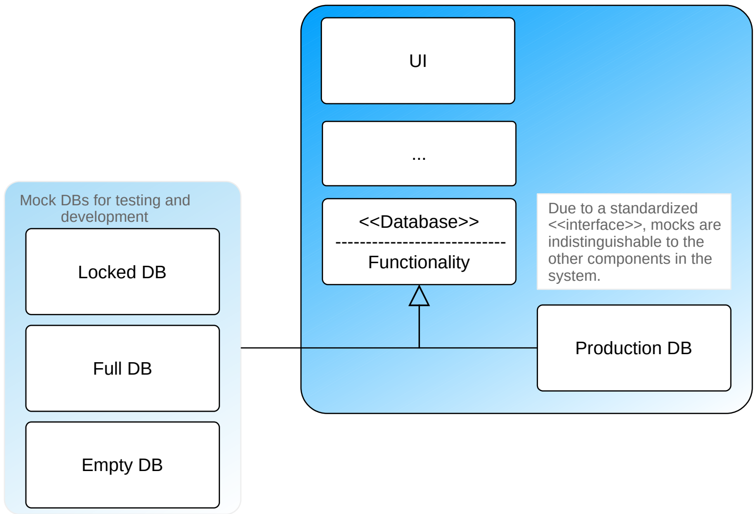
Existing challenges with controlling human systems are the lack of a ground truth. That is the internal state can only be relatively quantified. Mathematically this show’s up as an ill-conditioned problem, having several solutions. In the real-world, it shows up as different effects of the same states. For example, PERCLOSE (percentage eye-close) [perclose] and instrumentation (steering wheel and chairs) are good estimator of fatigue [83], [86]. Yet, it was observed that seasoned long distance drivers experiencing micro-sleeps stabilized steering wheels with their legs [82].

5.3 Digital mocking pattern

Mocking involves using a model to test or develop a system component under specific considtions (state). Typically a mock component is substituted for a production component through a standardized interface. This has the effect of testing the system response under a specific state.

An interface hides the substitution making the mock indistinguishable from the actual component.

Mock database example



Mocking involves using a model to test or develop a system component under specific conditions

The database (DB) example illustrates how different states of a DB are tested without modifying the production DB. This allows testing and development of an empty, full, or locked DB without disrupting production.

6. Conclusion

7. References

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8. Orphaned Deletable content

8.1 Background

> "There is nothing new under the sun; it has all been done before" ~Ecclesiastes 1:9

Manufacturing systems, like any progressive technology or field, have experienced several paradigm shifts. Sometimes from one extreme to another. From its organic beginning in cottage manufacturing of blacksmiths making custom weapons to evolution-based systems of system approaches like holonic manufacturing. The path from the efficiently structured assembly line to the flexible manufacturing system, only to arrive at some midpoint of reconfigurable manufacturing. One would easily argue that these paradigm shifts are simply a way in the waves of exploration and amount to nothing more than a change in focus and terminology. I share the interpretation with others [the author of general systems thinking], that these "paradigm shifts" do more than place emphasis on a specific area. They also serve to distance us from the previous innovations that have become so comfortable.

For this reason, it is necessary to briefly visit manufacturing paradigms related to Industry 5.0 and its emphasis on human-centricity. We avoid dichotomy, lumping relevant concepts like digital twin, simulation, and virtual manufacturing together. To some readers this may seem brash, assuming the previous generation of techniques are solved. I am of the view that progress in systems must be built on existing knowledge, not a reductionist or mechanistic approach.

8.1.1 A brief evolution of manufacturing paradigms

Craft production was the initial model of pre-industrial manufacturing, which was constituted by making products, one-by-one, and without the aid of tools. This resulted in a product based on the customers exact needs and utilized labor intensive process to develop hand crafted goods. Craft production survives for hobby and luxury products but does not scale well. Mass production is characterized by low-cost manufacturing of large volumes of products and was achieved by developing highly structured manufacturing systems with low flexibility that leveraged natural energy to drive production. Mass production saw boosts with the energy revolutions starting with steam, moving to electricity, and more recent developments in renewable energy encourage decentralization and small-scale systems.

Along the way lean manufacturing, 3 sigma, and Kaizen encouraged waste reduction by improving through waste reduction. This led to continuous improvement, where manufacturing systems are no longer static eternal structures but can adapt to the market needs.

Naturally, this iterative improvement encouraged a transformation from dedicated to flexible manufacturing lines motivated by mass product customization in the 1980-2000's. These again arrived at the conclusion that flexibility resulted in excessive cost and reconfigurable manufacturing addressed this by providing a hybrid between flexibility and efficiency-of-scale.

8.1.1.1 Architectural changes

Conway's law states, the organizations structure will mimic its communication structure, hence advances in communication technologies shape the way manufacturing systems are designed. These are best motivated as means to limit complex interactions. Advances in information technology have allowed manufacturing interconnectivity that has the potential to measure production efficiencies at a visceral level, while advances in control can address these issues in real time. To manage these complex interactions a systems of systems approach favors dividing into manageable subsystems like cells, to limit the interaction between subsystems. Where cellular manufacturing relies on tight interaction between cells, modern IoT and cloud-based manufacturing architectures separates tight hardware interaction for material handling from general information/communication interfaces in manner that is more in-line with cybernetics at the systems level.

While all these technologies have been realized in Industry 4.0, we have forgotten the simple truth that "all systems serve humans".

Paradigm	Emphasis	Driving forces
Industry 5.0	Human-centric	Economic, Societal empathy
Industry 4.0	Technology	Internet, Energy, AI/Machine learning
Circular Economy	Reusing and maintaining products	Product as a service
Green manufacturing	Resource efficiency, local production and use, waste management, green infrastructure	Sustainability, Ecological impact

8.1.1.2 Industry 5.0 and human-centric system

Industry 4.0 is technocentric, utilizing technological advancements like IoT, Digital Twin, AI, etc. for autonomous and productive manufacturing systems. Yet human labor plays a crucial role in manufacturing assembly. The automobile manufacturer, Tesla famously attempted to remove automate human labor, later admitting it as a mistake of "excessive automation"[cnb].

On the other hand, when augmenting human labor with technology we have seen an increase in productivity and quality. In the same way that smart-keyboard autocorrect increases your typing rate while decreasing typing errors, a human-centric perspective increases productivity in manufacturing. This is true for physical labor (Industrial ergonomics) but is becoming increasingly important for cognitive tasks as the role of human becomes more advisory. [] makes a compelling argument that previously sailing/seafaring used to be labor intensive, where now large few operators supervise highly automated equipment through LCD screens. They suggest that this may be the case with shipping accidents, happening late at night requiring decision making and cognitive tasks to execute. Therefore, the move from techno-centric to human-centric design is well warranted.

Even in environments with high levels of semiconductor industry, we will likely not see high levels of automation in manufacturing, medicine, or engineering anytime soon despite a few attempts [10.3390/app12157645]. Hence the emphasis in Industry 5.0 is human centricity, placing the operator at the center and developing technologies that increase the operator's productivity, comfort, and value.

Figure of operator 5.0.

Industry 5.0 is a practical effort motivated by economic, sustainability, and resilient factors. For example, manufacturing assembly accounts for 6/8 of Made-in-China-2025 [China25] target markets still use manual assembly. Circular manufacturing and products-as-a-service prolong the lifetime of products through manual repair, addressing sustainability. Green manufacturing favors manufacturing, assembling, and repairing products near to their point-of-use; increasing resilience against transport and labor disruptions. It is well known that assembly accounts for more than half of the cost of manufacturing in most industries. [Boothroyed] goes a step further and highlights that high levels of automation can result in products that are challenging to assemble, increasing overall cost. This illustrates that concentrating on technologies instead of value added can be counterproductive. Additionally, cost has little to do with interpreted value or demand, as can be seen by publicities effect marketing products that are "green", "sustainable", or "eco-friendly".

8.1.1.3 The relationship between manufacturing systems and software engineering

Manufacturing systems and software engineering have enjoyed a somewhat unseen relationship for decades [adiga]. From standardized interfaces as used in object orientated design, to automata and their similarity to holonic manufacturing, through to modern trends like virtual, digital, data and cloud-based manufacturing. The synergy between the two fields is clear. A likely contributor to the manufacturing industry being quick to computerize, digitize, and automate.

Another interpretation is the imitation of flexibility. While most interpret software as code, a more abstract interpretation is that *"software is a layer that is easy-to-change, as opposed to* *hardware being difficult to change"* [clean architecture]. This places software engineering as a system design approach that attempts to isolate the effects of change. Hence software engineers refer to "development" as an ongoing process including the post commissioning stages like maintenance, like continuous improvement in manufacturing. The aim here is to yield this flexibility of software to allow flexible manufacturing systems with the tools gained for our software counterparts. To this end, we borrow the Unified Modeling Language (UML) to describe our architectural choices and patterns.

8.2 Human state estimation via observer, sensors, and virtual sensors

8.2.1 I4.0 to I5.0 virtual sensors, VR, HMI

In some ways, Industry 5.0 acknowledges I4.0 reaching maturity. The techniques developed in I4.0 require creative innovation to be utilized in a human centric manner. One case is using "digital twins for development". For example, when developing robotic applications, high-fidelity simulations are used [like the robot operating system ROS and unity]. These typically simulate physical interactions. We gain the capacity for human-machine interaction by adding VR these simulations.

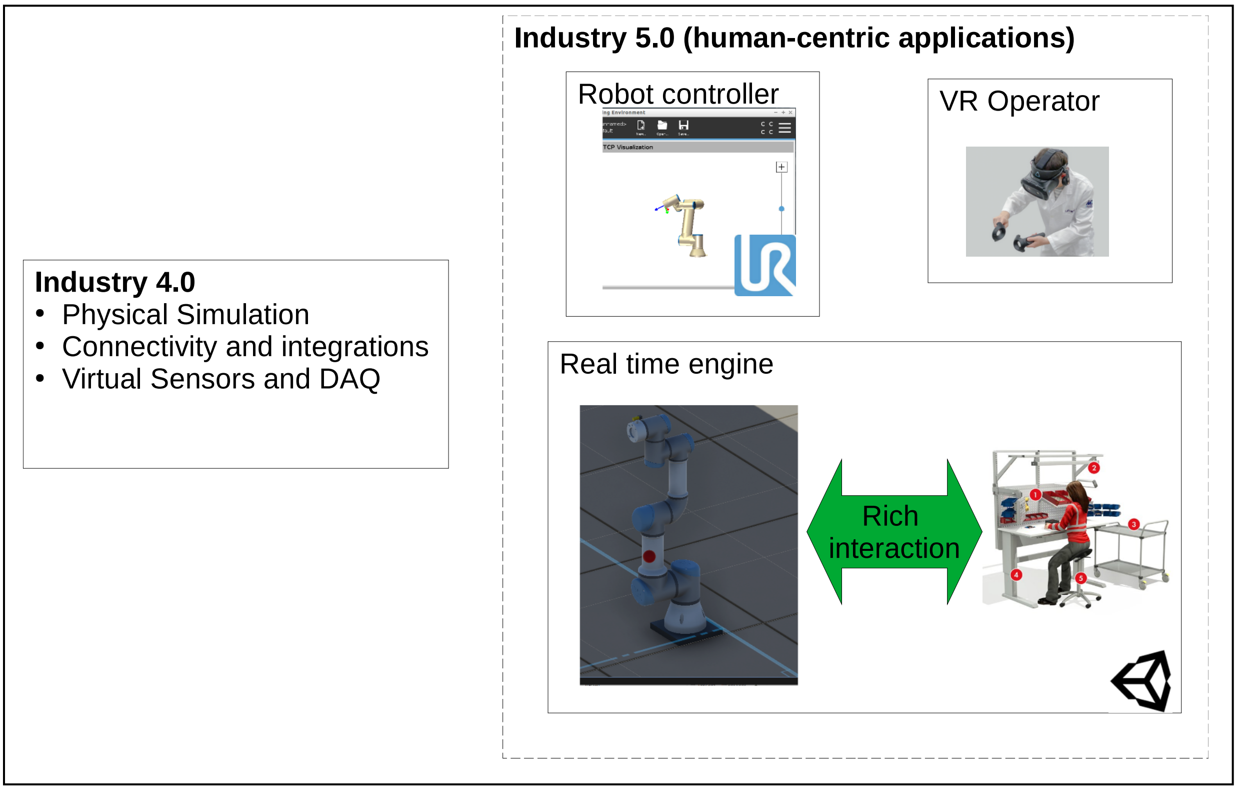
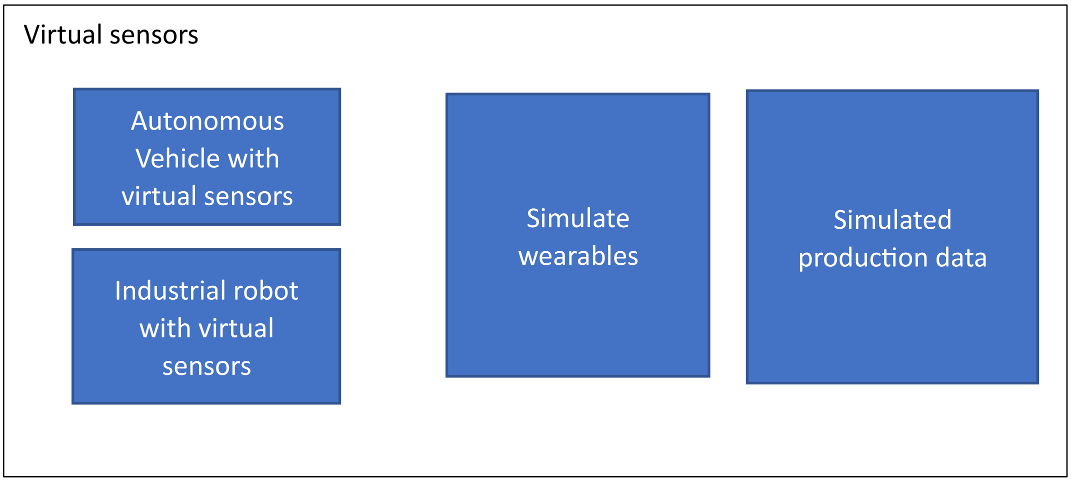


Figure 21: Industry 4.0 developed techniques for simulation and connectivity of devices. Industry 5.0 emphasizes realizing these in a human-centric way. Here VR enables including humans into the rich simulation environments developed.

VR can also facilitate the development of human centric virtual sensors. In robot It is common practice to develop robotic applications/systems using virtual sensors. This has become particularly apparent in autonomous vehicle applications where simulated environments are used to develop data-acquisition systems for training machine learning models [Automatic generation of synthetic datasets from a city digital twin for use in the instance segmentation of building facades]. However, it is not clear how this technique will be leveraged for human centric systems. A naïve solution may simulate wearables, but wearables reduce operator comfort, hence the cost of sensing is not free. In contrast this work shows that production data (like throughput rate) contains valuable data for human systems. A sensory fusion between wearables and production data may be necessary. Here virtual prototyping provides a means of investigating these questions to develop creative solutions.



Yet applying this technique to human operators presents a few well-known problems. Firstly, the **human machine interface** is considerably more complex, with entire journals actively researching the topic. Secondly, human behavior/performance models are significantly more complex than their machine counterparts, owing to their dynamic, uncertain, and interacting (non-linear) nature.

8.2.2 Virtual manufacturing systems

Discrete event systems are typical for simulating manufacturing systems to identify bottlenecks, performance, etc.

Due to the high level of abstraction, limitations exist:

- real world data is required to calibrate these models.

High fidelity simulation environments (digital twin, virtual factory, etc.) address this limitation at the cost of complexity. These environments:

- Facilitate development of electric, control, and communication [virtual commissioning of manufacturing systems, Industrial Robot]
- Reduce financial capitol risk with virtual prototyping.
- Reduce development risk by identifying technical issues early.

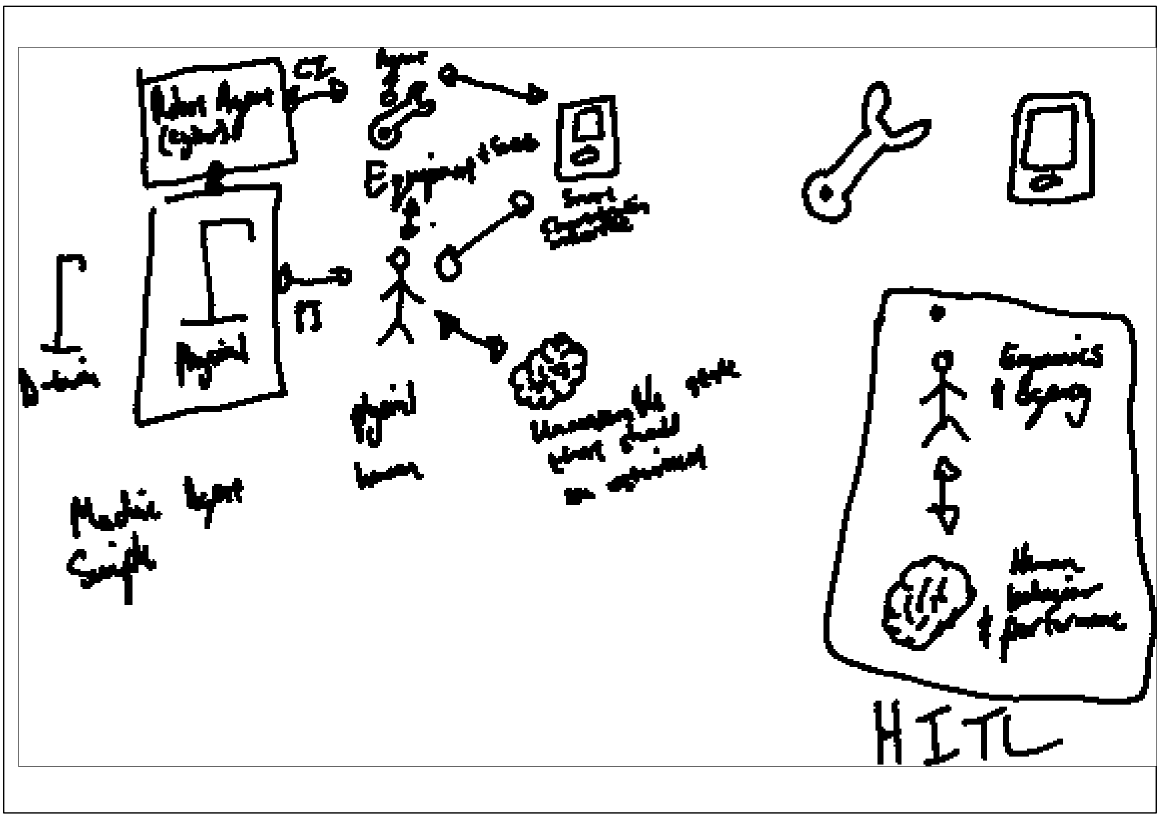
- Facilitate vendor neutrality and long-term support.

Issues of HFS:

- Complexity as these involve interacting software.
- Distributed simulation and network issues

Figure x: contrasting DES with virtual manufacturing

8.2.3 Separation of cyber physical interaction, digital twin, and VR



This section presents an architectural interpretation that separates cyber from physical interactions. Explicitly separating these reduce the complexity of systems by separating control from physical interfaces,

, we can develop these interactions in isolation, limiting complexity and increasing reusability through modularity.

By illustrating these challenges and how human-in-the-loop simulation simplifies this architecture to a point where it allows us to utilize the techniques designed for I4.0.

Separating cyber and physical interactions

This technique has been implicitly used in developing agent-based systems [Industrial robot and Letaio], robotic applications, and in some sense, general manufacturing systems. For example, physical interfaces like flanges, fasteners, and robot grippers are separated from IO-communication interfaces like CAN or Profibus. Similarly, some robotic simulation packages allow us to develop robot code without considering physical interfaces (Robot-DK, KUKA-sim, etc.). Finally, agents and simulation often hide/wrap the complexities of communication interaction. These examples illustrate how this separation between cyber and physical interaction is implicitly being employed.

These separations may be critical in planning data-acquisition, data-based modeling, and data-based control modules. Data acquisition is a crucial part of modern manufacturing systems for assessing performance. Similarly, it is predicted to be crucial in modelling behavior and performance [IFAC-Industrial ergonomics 4.0]. Also, it is a requirement for control of human systems like dynamics scheduling.

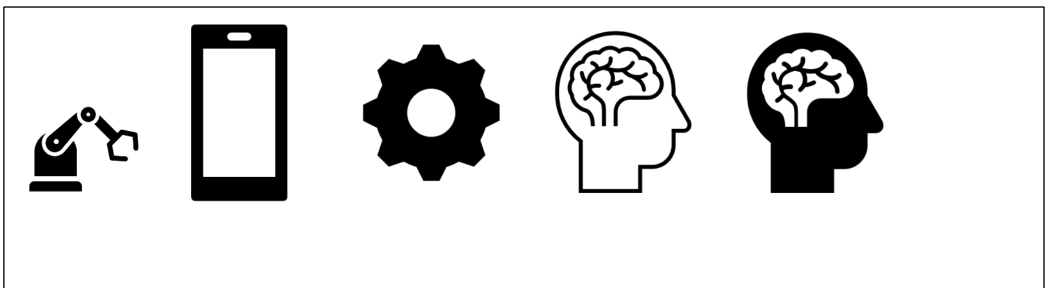
For example, the data may be used to calibrate high-level DEVS simulation models. In contrast, low-level dynamic scheduling will require access to real time data. To further complicate these decision, data-security and privacy issues restrict the application and exposure of data.

For example, the UN

The presented architectural diagrams are simple enough for management and policy makers to understand the choices made, while retaining sufficient technical detail to motivate data-locality for control or prediction requirements.

Separating the physical and cyber interactions aids in designing the human-machine interface. A human operator typically has physical interactions like part handling and cognitive interface like touch screens. Deciding between an operator-specific or shared workstation will affect login system, the locality of data, and the interactions with the network. Again, these decisions influence the complexity of the solution, but the diagrams simplify communication.

These diagrams highlight which interfaces/interactions will be simulated in VR. This results in deciding what communication interfaces are required.



8.2.4 The need for a development procedure moving to industry 5.0

Human-centric design was so pervasive because we understand the world in human way. Recent advances in technology have pushed our understanding to ever higher levels of abstraction. For example, a book and pen offers a simple few affordances. In contrast a smart device with a pen has several apps, states, and interfaces such as touch, buttons, and pen that we are exhausted before we start writing. A concerted effort should be made to present solutions in a human-centric way.

Turning our eyes towards Industry 4.0 we observe this techno-centric approach emphasizing abstract concepts like Digital Twin, IOT, Systems of Systems, etc. These concepts speak little to the human experience and often leave us imagining or confused. VR on the other hand places humans in the familiar temporal-spatial environment, resulting in a deeper understanding and appreciation for human affordances and the HMI.

As an illustration of VR's place in the transition from I4.0 to I5.0 a prototype was developed. Industrial robot 3D simulations have been extensively used. They supply high fidelity real-time visualization of the working environment, facilitating development in safe and flexible environment. When placing a VR operator in this same environment several possibilities naturally present themselves. First of all human robot interaction becomes practical and safe. Here the human can manipulate the robot. Secondly the human trajectory can easily be recorded and imitated by the robot. This has the advantage of delaying the need for specific trajectory tracking sensors. Thirdly this rich interaction provides meaningful feedback to the human, data for modeling, and feedback for the developer. These motivate VR as an environment for developing creative application of I4.0 concepts.

TDD and other development procedures:

- Simple and obvious
- Emergent design properties

The changes that have are becoming evident

The difference between I4.0 and I5.0

8.3 Investigation overview

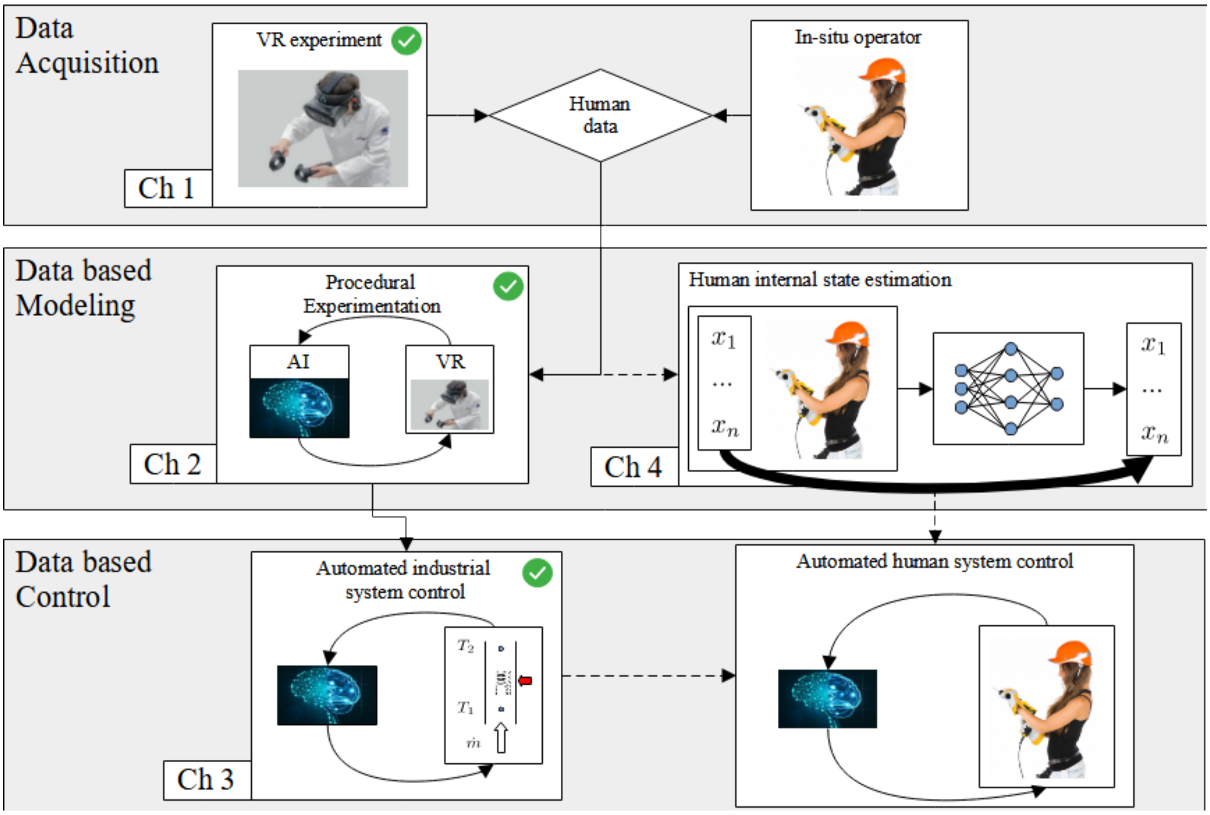
This section serves as a verbal table of contents. This thesis is structured as a series of investigations, one building on the other.

In order to develop human centric systems using virtual reality, we must first confirm that VR is suitable for measuring the human state. Therefore, this investigation starts with the question "Can VR measure human assembly performance?". We investigate this by measuring the task duration, chance of assembly error, and assembly tolerances. Once we have established that VR simulations can measure human performance, we explore two paths. Firstly, an application of the newly confirmed VR simulation. Secondly, an investigation into sample efficient experiments using VR simulation.

To apply the VR simulation, we consider part-consolidation via additive manufacturing and how it affects assembly time. Here, additive manufacturing allows printing components together, resulting in several configurations for printing that must be assembled by an operator. The cost of assembly and cost of printing are balanced to select the best configuration.

To investigate sample efficient experiments, we use the VR simulation as a platform to develop optimal experimental tools. Using a model and human-in-the-loop simulation, we can determine the throughput rate with fewer experiments. This reduces the overall cost of VR simulation, making it more practical. It also illustrates that VR can be used to develop data-based systems.

This led to more general insights into developing data-based human-centric AI systems. Firstly, deep learning has the potential to estimate the human-state using data from VR. Secondly, AI can be used to dynamically control human assembly schedules. The issue is the two seem to be complementary. In order to ethically control a human system, the internal state must be considered. Thus, an ethical solution cannot consider control without the human internal state.



Data Acquisition
VR experiment
Ch 1
Human data
In-situ operator
Data based Modeling
Procedural Experimentation
AI
VR
Ch 2
Human internal state estimation
x_1
...
x_n
x_1
...
x_n
Ch 4
Data based Control
Automated industrial system control
T_2
T_1
$\dot{m}$
Ch 3
Automated human system control

9. Human internal state estimation for manufacturing as blind source separation using a dynamic auto-encoder.

9.1 Abstract

Human internal state affects operator well-being and production outputs, but it cannot be directly measured and must be estimated. This paper proposes a deep learning approach to unsupervised nonlinear hidden state estimation using an auto-encoder, by framing it as a blind source separation (BSS) problem. The model is composed of a dynamic auto-encoder-based and extended to blind source separation using local losses to decorrelate hidden signals. The number of sources can be determined by adjusting the dimension of the hidden state signal. Simulations demonstrate hidden state extraction when the correct dimensionality is selected and separation of multiple sources. Using an auto-encoder in the model restricts it to cases where there are more sensors than hidden states. This makes it well-suited for domains with redundant sensors, such as drones and self-driving cars.

9.2 Introduction

Human-centric systems are actively being researched, as evidenced by several recent special issues [1]–[3], an EU report [4], and the rising cost of labor in manufacturing. This requirement, along with rapid change in systems encourages the use of automated/unsupervised approaches. However, these approaches are limited in their application of human control due to ethical issues.

When optimizing human operation systems we are presented with the challenge that “Systems Serve Humans”. Therefore, these systems must balance production requirements with the well being of operators. The authors believe this is possible by controlling systems based on human internal state variables like fatigue.

This work is the starting point of investigating automatically extracting the human internal state. The problem is formulated as a blind source separation problem. A nonlinear deep estimator is developed to extract the unmeasurable states. The main objective of the current investigation is to develop a model that meets the requirement to extract the human hidden states. Capable of time-varying and state interaction, or simply nonlinear dynamic.

The contributions are:

1. Development of a dynamic nonlinear model with time-varying and source interaction capabilities.

2. By formulating image generation as a BSS problem, we gain cross pollination of methods, leading to insights that motivate the models development.

9.3 Literature

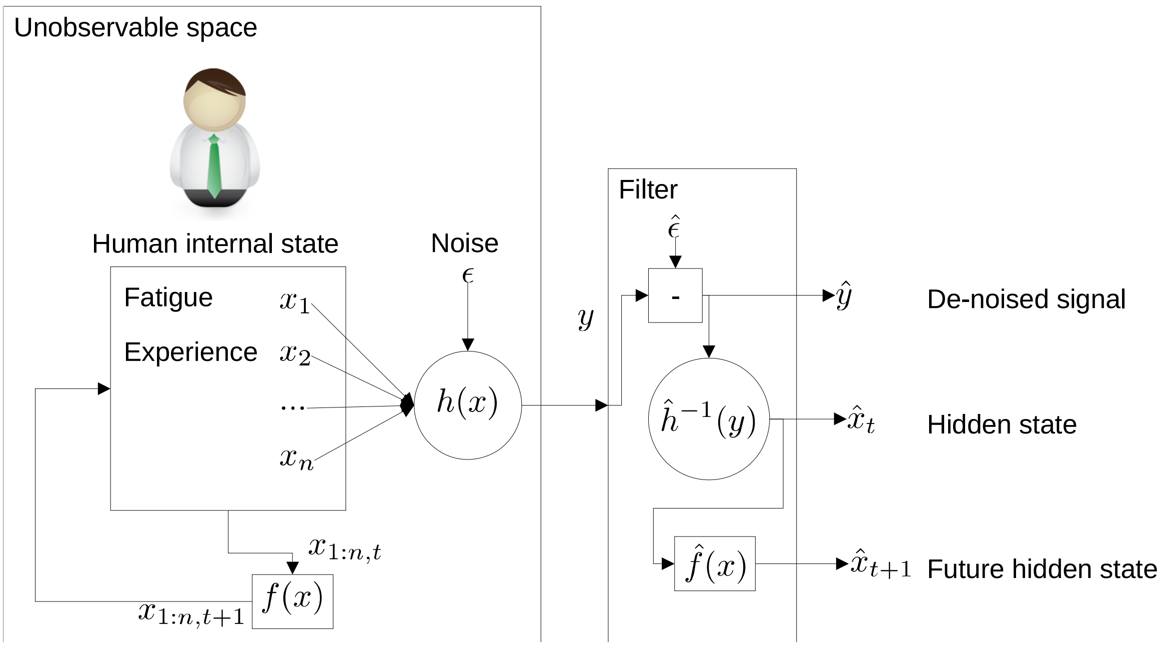


Figure 22: Human state estimation as a dynamic problem showing estimator requirements

9.3.1 The importance of human unmeasurable states

States like fatigue cannot be measured directly, instead they are estimated by measuring their effects. Sensing can be accomplished either by gathering data from the operator or by measuring the impact on production signals.

9.3.1.1 1)Operator sensing

Industries with static operators (pilots, long distance drivers) have seen successful commercial products using operator facing cameras and integrating sensors into instrumentation.

However, industries with dynamic operator tasks (manufacturing and seafarers) have not enjoyed the same success. Wearable sensors like accelerometers, EMGs, and temperature sensors [10] have been used in lab experiments, but hinder operator comfort. Biological samples like oral swabs [11] are accurate, but not suitable for in-situ sensing.

The issue is that many of these data acquisition methods are not feasible for in-situ sensing and it is not clear whether the information provided overlaps.

9.3.1.2 2)Production data signals

Fatigue negatively impacts production outcomes but does not provide information about the underlying causes. However, it can be used as an indicator to estimate the human state.

For instance, factors such as time of day and consecutive work days are strong indicators of risk of injury [5], [6]. This hints that there are multiple modalities to fatigue. We expect one source for daily fatigue and another for weekly fatigue. Another example is that learning increases operator's throughput rate, while circadian rhythms [7], forgetting [8], work-rest ratios [9] decrease it.

Human state estimation is important for human well being as it can reduce risk of injury and production because it can affect production outputs. The examples illustrate the model should be (1) dynamic, allowing time varying signals and (2) nonlinear, allowing hidden state/source interaction.

9.3.2 Blind source separation

The blind source separation problem is sometimes better described by the cocktail party problem. Imagine numerous people talking, resulting in the recipient receiving a mixed sound signal and having to discern between different conversations. The authors use this term as a problem formulation rather than a collection of methods. BSS methods have been used for audio source separation [12] and signal processing [13].

BSS is often an ill conditioned problem, resulting in numerous solutions. Specifying further constraints has the potential to reduce this. In some cases, the signal can be recovered but not the amplitude. However, this limitation can be overcome by using a number of local losses, which will be discussed shortly.

One technique for achieving BSS is Independent Component Analysis (ICA), an extension to the well known Principal Component Analysis (PCA).

9.3.3 Deep blind source separation as high level feature separation

The authors argue that deep learning makes it possible to represent several high-level tasks as a blind source separation (BSS) problem. Among these, image processing and generation techniques are the easiest to visualize. This insight is valuable for conditioning the latent space, as high-level feature modification is often necessary to generate new images.

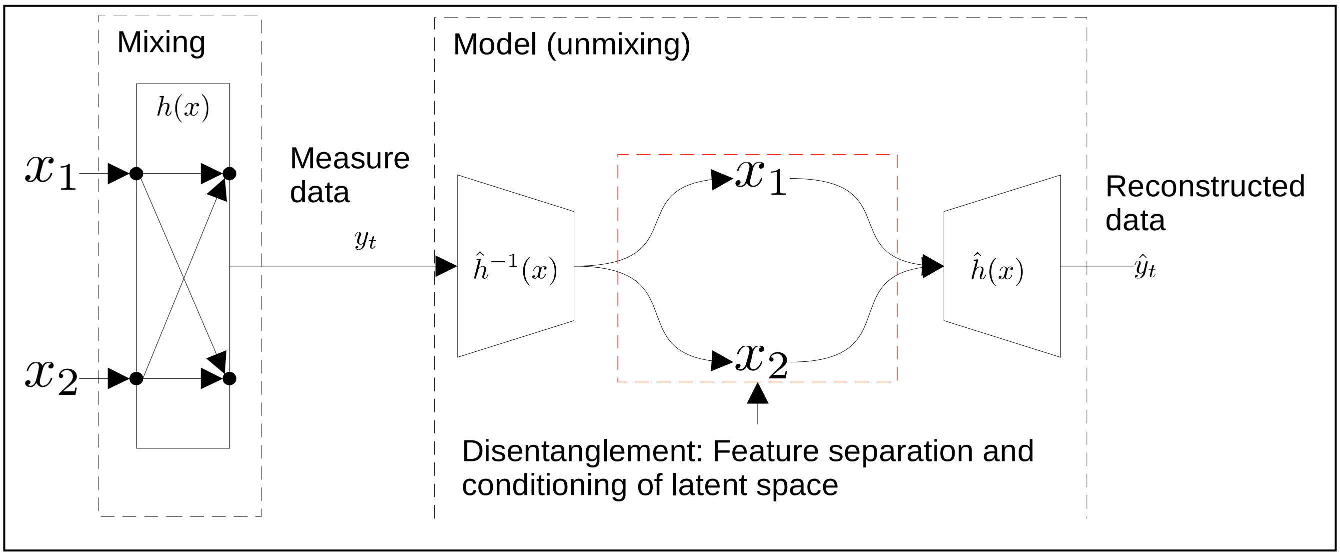


Figure 23 Deep blind source separation using an auto-encoder showing disentanglement of the latent space.

For instance, [14] separates facial identities from emotions to reconstruct faces with different emotions, [15] separates blur, noise, and compression image distortions, and Fader networks [16] allow sliding attributes to adjust the feature intensity, such as transforming from young to old.

Disentanglement refers to the linear separation of features, styles, and other information in the latent space [17], [18], which is similar to source separation. Several methods have been used for estimating disentanglement such as, developing a linear classifier [19], using cluster separability [20], applying a probabilistic total correlation penalty that requires sampling [21], or using a discriminator [16]. While auto-encoders are commonly used for this problem [17], [22], [23], some models do not employ them [18], making disentanglement comparison difficult.

9.3.4 D. Hebbian learning inspired local losses.

One neural learning algorithm which has shown lots of promise in this area is Hebb learning. Although it is not used in this work due to back-propagation tools being more mature. The insights found in Hebb learning motivate the choices for local losses here.

Hebbian learning is best described by the adage "Neurons that fire together, wire together" [24] . The Hebbian learning interpretation of this strengthens of pre-synaptic and post-synaptic pairs that fire together. This results in learning the principal components [25]. On the other hand, Anti-Hebbian learning weakens pre-synaptic and post-synaptic pairs that don't fire together, resulting in decorrelation which can be used for BSS [26], [27]. This Anti-Hebbian learning can be imitated using an auto-encoder with the inappropriately named Decov loss [14], [28].

Hebbian learning has also addressed some of the other limitations in BSS, by conditioning the source signals. Unscaled source amplitude is addressed by enforcing unit variance [27], this in turn inspires the use of unit variance local loss use here. Similarly, zero mean source signal is typically achieved by whitening the data, instead we use a small zero-mean loss.

9.3.5 Auto-encoder implications on sensor design

The auto-encoder is selected as the starting point for the model because there is strong evidence that it performs nonlinear Principal Component Analysis (PCA) [29]. The intuition here is to use decorrelation to move toward nonlinear Independent component analysis (ICA), one of the better known methods for BSS. However, the auto-encoder does place some restrictions on our sensor selection. It assumes that the number of sensor signals is greater than the number of source signals, where . This is not unreasonable since redundant low-cost sensors are often preferred over fewer high-cost sensors and provides denoising benefits.

9.3.6 Deep temporal estimators

Most BSS work considers static solutions. For example Fourier transform and have the limitation on time varying signals and latent state interaction. Formulating this problem as a dynamical system has the potential to relax these two limitation.

Well known estimators like the Kalman filter and extended Kalman filter have been widely applied. However, their linear limitations are known [30], [31]. Another generation of filters use computationally intensive monte carlo simulations to estimate nonlinear behavior [32]. Deep estimation techniques tend to incur this computational cost upfront by learning filtering parameters and estimating functions, resulting in cost effective inference. Here, the functions or parameters are learned. A desirable trait with deep filters is the ability to include prior known information , usually in the form of partially known dynamics [33].

9.3.7 Summary

To summarize, human state estimation can benefit human well being and production output. These models require time varying and interacting source capabilities. Due to the variety of sensing means, humans automated/unsupervised estimation will be beneficial. On the other hand, the ability to incorporate known dynamics is desirable.

Since the human state cannot be measured directly, we suggest modeling it as a BSS problem. By formulating deep image-processing tasks also as a BSS problem, we gain the insight that a decorrelated AE perform nonlinear ICA. Hebbian inspired local losses can address the limitations of ill-conditioned models.

9.4 Theory

The figure that follows depicts the decisions made when developing the model. Starting from a standard auto-encoder, moving towards a supervised temporal estimator, and then an unsupervised estimator.

We begin by developing the model, then describing the local losses required to shape the latent state.

9.4.1 Neural architecture and losses

The model is developed with three losses, starting from a standard auto-encoder with the reconstruction loss included.

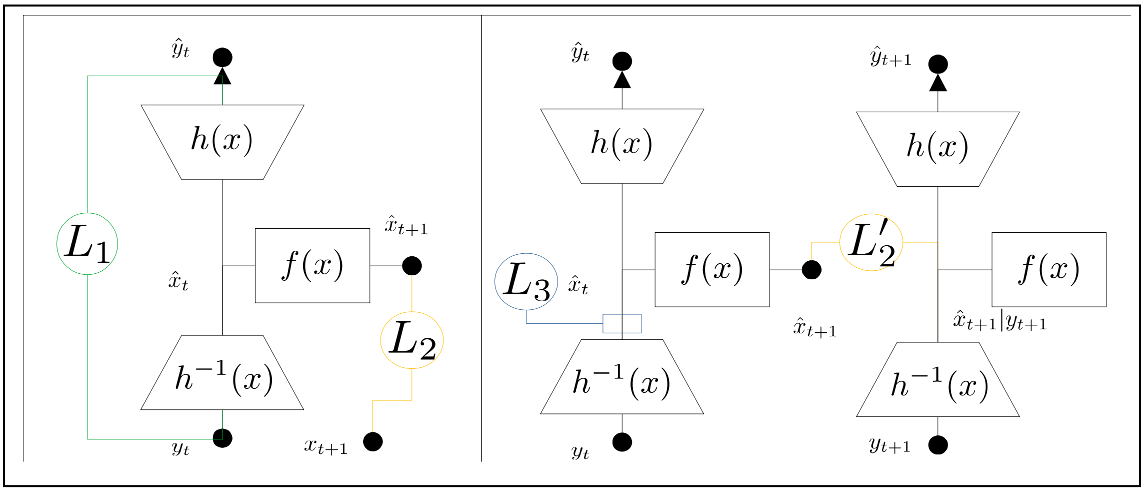


Figure 24 The stages of the estimator. From left (1) shows the supervised estimator and (2) the unsupervised estimator.

Next we create a supervised estimator by adding an evolution/transition function and loss. The figure illustrates this. Some important notes here are that (1) we assume our sensor dimension to be higher than our latent dimension. This is advantageous since it is common to have numerous redundant sensors for noise reduction, cost reduction, and reliability. At this stage we are presented with a choice. Ideally, the transition function is known and used. This work instead assumes an ANN is used. The hidden state data is used for training an ANN but in the next step, we lift this condition.

The final step is unrolling in a similar way to other recurrent neural networks. Here a loss penalizes the error between the sequential predictions of the model , specifically the encoded temporal-prediction from the current time and next encoded prediction . Figure 3 illustrates this. This change removes the requirement for the hidden state data , relying only on returning to an unsupervised learning problem. The cost of this is that batches of at least 2 sequential data-points be used. If the equation is known, it can be substituted for the neural network.

Since we do not supply the function, the model must infer it, which can result in several effects. Firstly, the dimensionality of x now becomes a design choice, meaning that we can decide how many variables to include in our input. Secondly, this is a poorly conditioned problem, which means that numerous solutions exist and we may not receive the same solution between multiple training sessions. In other words, the model may converge to different solutions each time it is trained.

9.4.2 Local losses

A widely accepted strategy to address the issue of numerous solutions is to calibrate the source signals to some domain, for example . In this work, we use a number of losses that are local to the mini batch used in training. First, a mean loss encourages zero mean. The second loss ensures unit variance.

A decorrelation loss disentangles sources , where . The intuition for this choice is moving from PCA to ICA. The resulting local losses can then be weighted and summed, .

9.4.3 The dimensionality of the latent space

Given this model, one design choices is to choose the dimensionality of , where . The dimensionality of , where , is dictated by the sensors. We will select such that we can learn more about the system.

In summary, we now have a model that is capable of dynamic estimation of sources with interaction. Although the model can incorporate known dynamics in the form of the transition function, this work is interested in inferring the transition. This introduces the dimension of the latent space as a design parameter.

9.5 Methodology

Two simulations are conducted. The first investigates the effect of selecting the dimensionality of the latent space. The second simulation investigates extracting multiple nonlinear sources.

9.5.1 Model

In order to evaluate the filters behavior they are tested on a toy problem of one pendulum acting as a single source. The state is generated by the system transition . The model receives the sensor signal which is mixed and noise is added according to . The goal of the model is to estimate the transition function and the state estimation function .

Two mixing strategies are considered. Firstly, independent nonlinear mixing, via , which tests the models ability to perform nonlinear estimation. Next, a nonlinear combination mixing, , testing source separation. These sensor models significantly change the signal and do not allow negative values in these simulations. This has an impact on the resulting transition function.

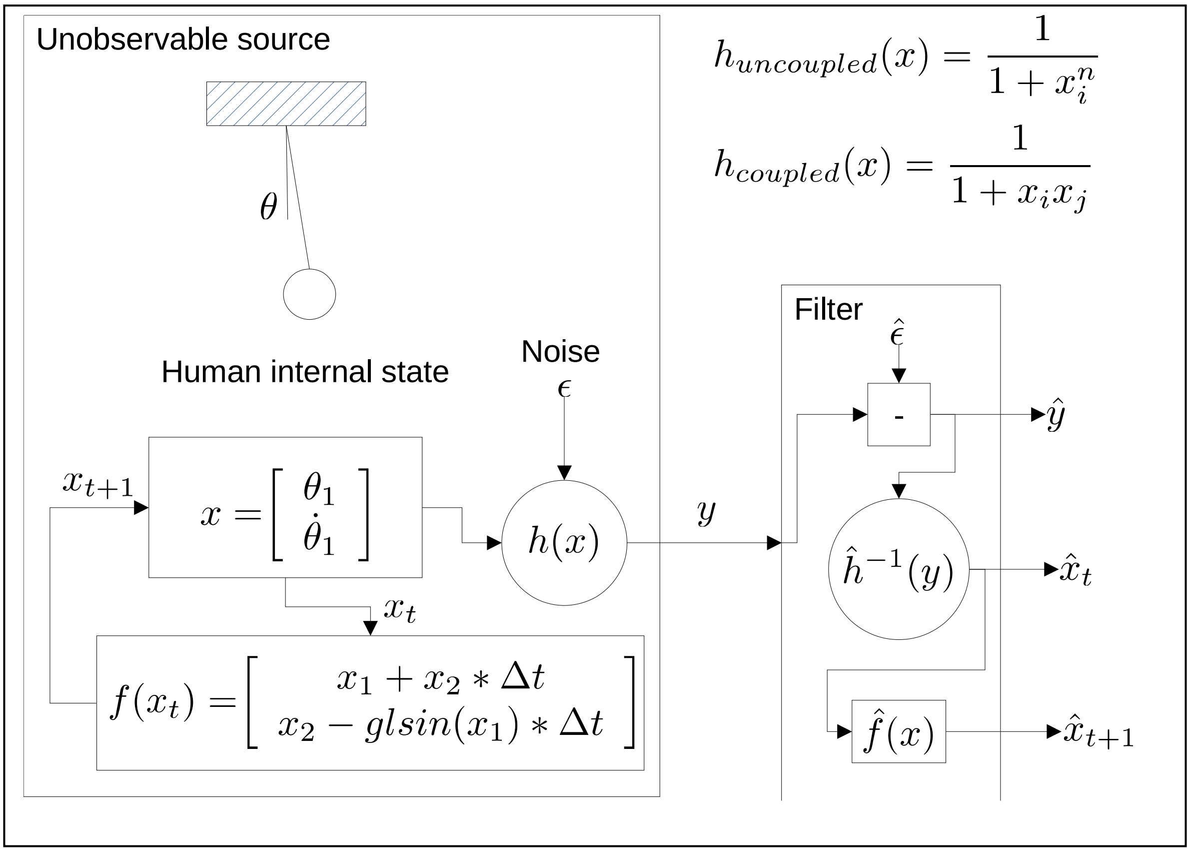


Figure 25 Simulation used for testing model

We explore the selection of the latent space and encounters the repeated signals issue.

9.5.2 Multiple sources

Next a system consisting of two sources at different frequencies are used. This section tests source separation.

A number of systems are used. Firstly, the pendulum is selected for its familiarity. Also the Van der pol attractor is selected as it can be tuned to represent nonsymmetric waves [34]. Finally, the triangular wave it used due to its discontinuous nature.

9.6 Results

9.6.1 Single source pendulum state estimation

As expected, the model infers principal signals. The leading and lagging relationship between the position and velocity was learned. We also see that noise is present in the result, it is unclear if regularization can improve the results. The relative increasing magnitude is also captured, showing time varying signals are captured.

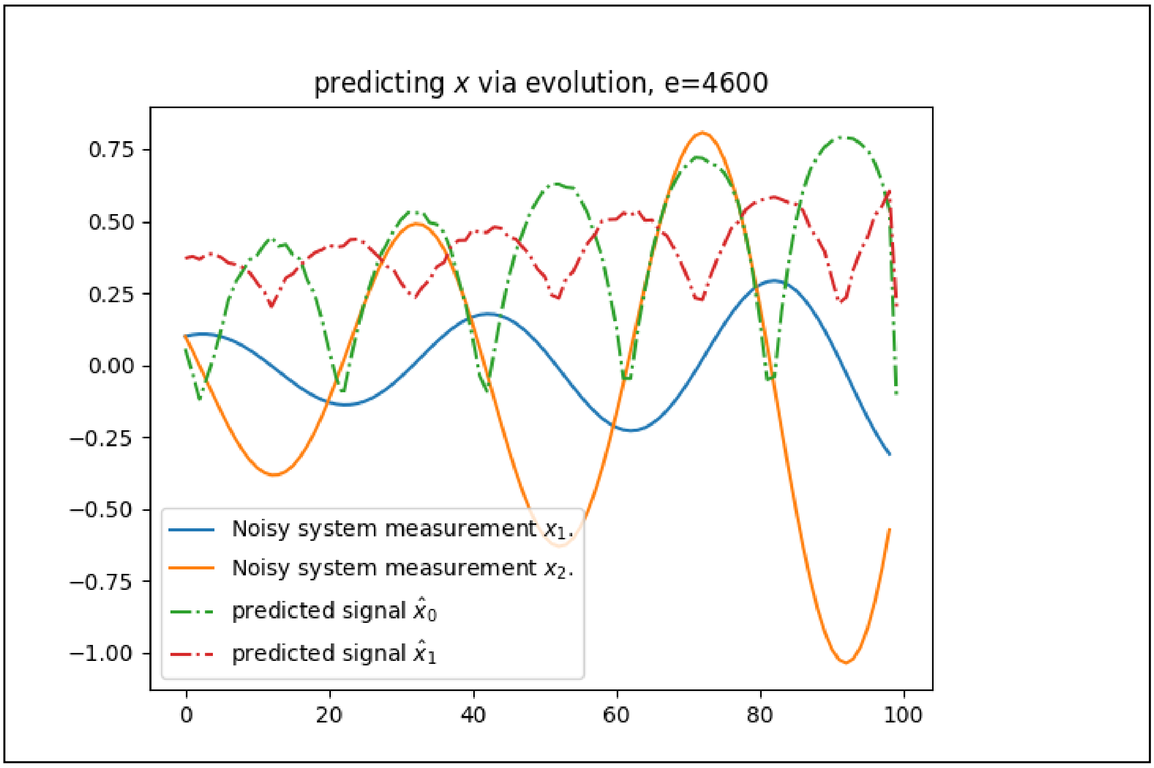


Figure 26 The model successfully estimates the two hidden states (position and velocity) of the pendulum.

This result would indicate that the model is sufficient for decoding and predicting some indicators of the hidden state.

9.6.2 Varying the latent space dimensionality

In our experiments, we observed that when the number of source signals (n) is equal to 1, the resulting signal was unique, meaning that different runs with random initialization produced the same output signal. However, when n>1, the results were not unique, and tthe signals' mean and sign would vary. Furthermore, when n was increased beyond 2, repeated signals occurred, which is likely due to the presence of repeated principal components. Therefore, identifying unique signals can be used to select the appropriate principal dimension size for a given dataset. Currently, this process is often done through visual inspection, which can be time-consuming and subjective. Therefore, automated approaches should be investigated to improve the efficiency and reliability of this process.

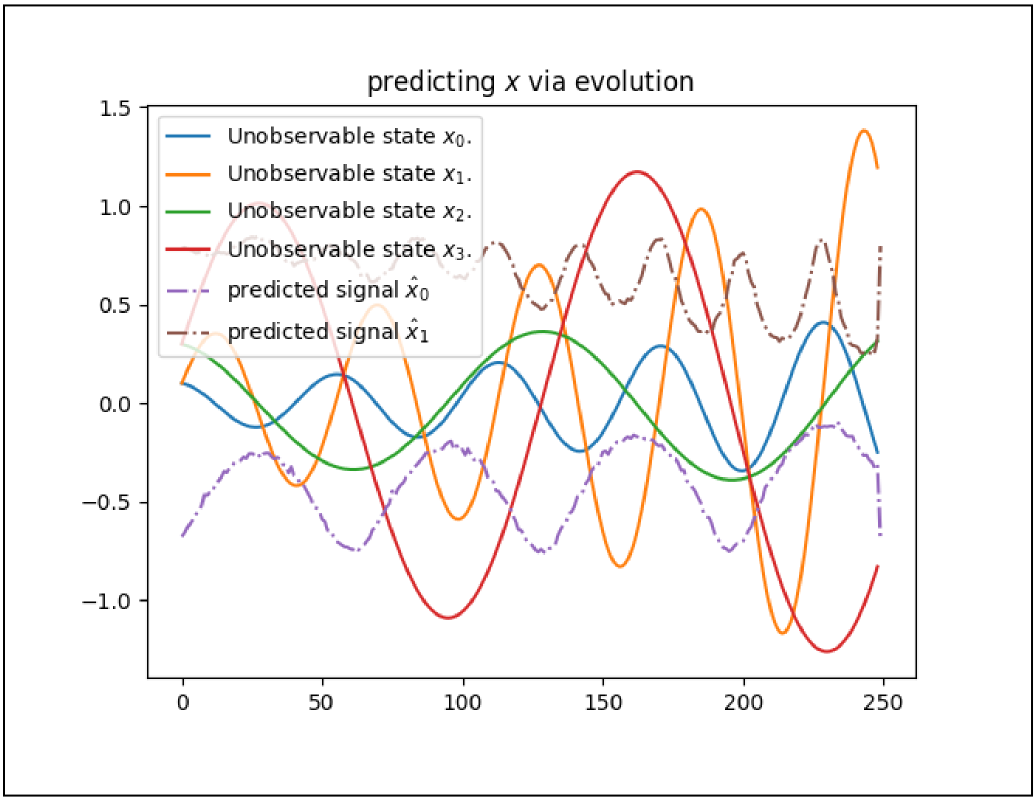


Figure 27 Repeated principal signals are estimated. The authors notice this happens when the dimension of the latent space is too high.

9.6.3 Source separation

The process is repeated with multiple sources and decorrelation added to the model to determine whether the model can perform blind source separation.

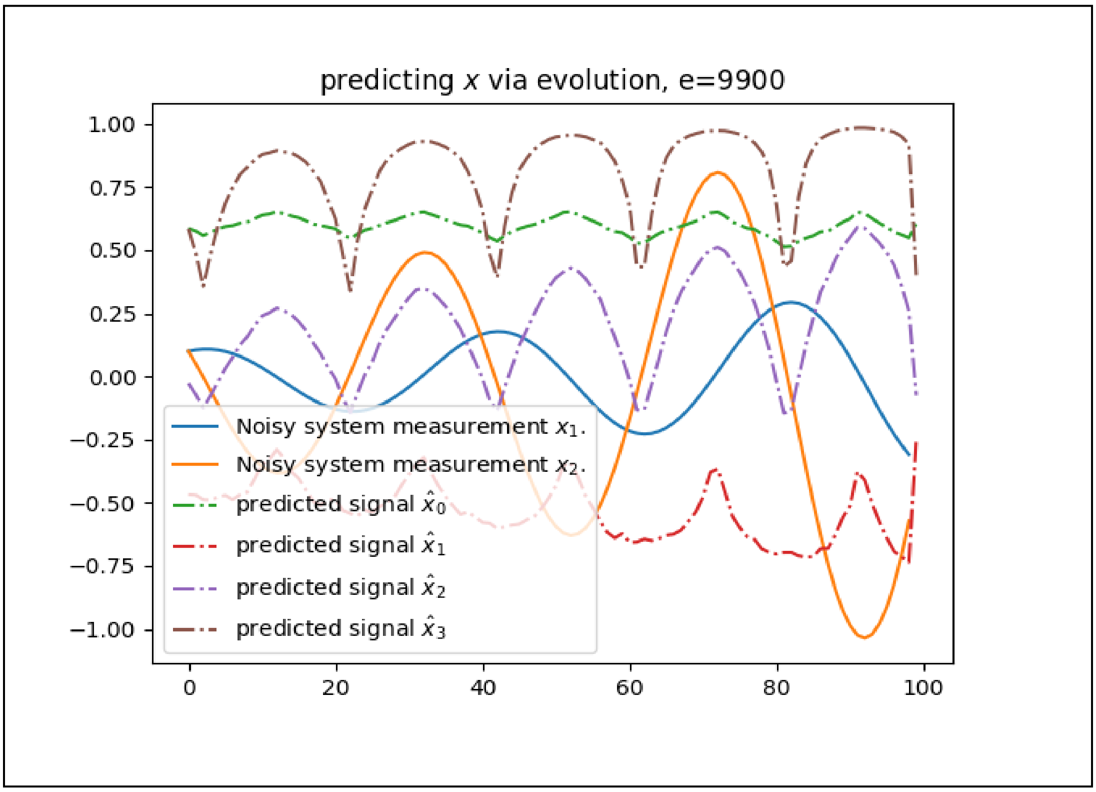


Figure 28 The model performing source separation.

The figure above clearly shows that the separated signals are observed. It is also clear that signals are affected by noise. Again, the amplitudes are not repeatable between runs.

9.6.4 Common systems

The triangular wave was also reproduced, showing the model can learn signals that are not smooth.

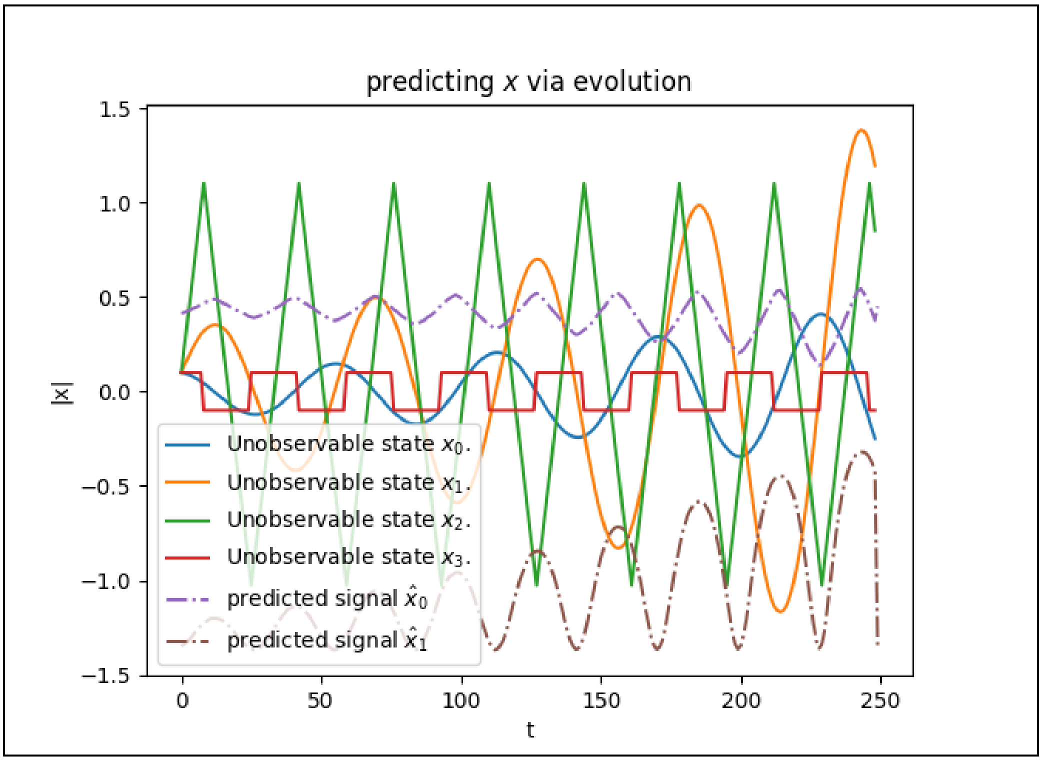


Figure 29 The model separating a triangular wave which has sharp discontinuous peaks.

A Van der Pol attractor was used, and the model was able to reconstruct these signals. Showing it can model nonsymmetric waves and limit cycles.

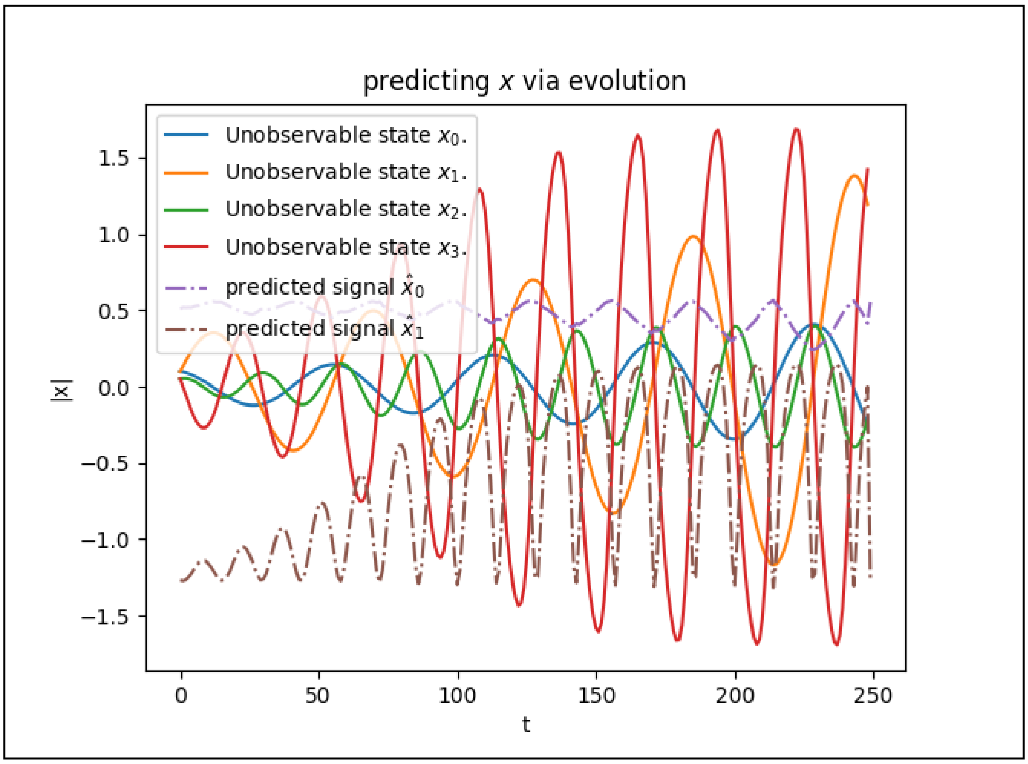


Figure 30 The mode separating a time varying, nonsymmetric Van Der pol attractor.

9.6.5 Conclusion and further work

In conclusion, estimating the human state can improve operator well-being and increase production throughput. Using examples from literature, we have determined that the model for human state estimation should be capable of handling nonlinear dynamics. Formulating the task as a blind source separation problem resulted in a dynamic auto-encoder model that meets these requirements and can infer hidden states in an unsupervised manner, with the option of incorporating prior information in the form of a transition function. The dimensionality of the hidden state was selected based on visual inspection, which is suboptimal and requires further research to develop a more effective selection method.

9.7 References

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Acknowledgements

This journey would not be possible without the support of so many people. *"It takes a village to raise a child" ~African proverb*. Similarly, *"it takes a functioning society to complete a PhD"*.

First and foremost, I would like to thank my wife Simone for supporting me and blessing me with two beautiful children during this journey. *"A man has no greater honor than providing for his family"*.

To my parents Russel and Debra who fostered my fascination with science, technology, and problem solving and equipped me with the character to complete such a journey. I know this will make you proud.

I would like to thank my supervisor Namhun Kim for his mentorship, allowing me sufficient freedom to spread my wings, yet bringing me back on course when I have strayed too far is made possible only through trust, empathy, and wisdom. *"Steel molds steel, so one-man shapes another" ~ Proverbs 27:17*

Several mentors at UNIST for their help along the way. Duck Young Kim, Kang Hoon Sang, and Huyodang Oh. *"Interest begat knowledge, not the other way around"*

During my stay in Korea I am grateful to (1) the many students, staff, and colleagues at UNIST, particularly in the UCIM lab, (2) the Korean government, public systems, and public servants, and (3) the many friendly strangers encountered along the way.

"I will forever remember,

the mountains, the leaves, from green to brown,

the insect that buzz, all spring 'round

the river that flows, with monsoon pour-down

the brown bridge freezes slippery when winter comes round

a quiet place great minds go to think,

but don't wait too long, your stay will be over in a blink"

~My ode to UNIST

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