Digital mocking pattern for development of human-centric assembly systems

The advent of Industry 5.0 marks a pivotal shift from a techno-centric to a human-centric focus. In navigating this transition, design patterns emerge as invaluable tools, empowering developers to adeptly address common challenges by imparting structure to solutions, modularly separating components for reuse, and fostering a shared vocabulary that enhances communication.

This research advocates for the integration of a digital mock pattern into the development of human-centric systems. In this approach, a virtual workstation (digital twin) replaces the physical counterpart during development and testing. This substitution allows for the validation of assumptions and fine-tuning of a human performance model without changes in hardware.

The versatility of this pattern is demonstrated through its retro-reflection in three previously published articles, showcasing its adaptability to various tasks. These tasks encompass validating established models within specific domains, exploring novel models, creating sample-efficient dynamic scheduling systems, and devising decision frameworks that leverage human performance data.

Our findings underscore the applicability of this pattern to diverse case studies, emphasizing its flexibility. Additionally, we propose that its utilization fosters creativity by enabling the combination of components in a virtual prototyping environment that facilitates rapid iteration.

While acknowledging the potential significance of simulation and development costs, we emphasize the need for a case-by-case decision-making approach to ensure feasibility. Conversely, this methodology proves particularly flexible in domains where human-error risk is elevated, such as medical surgery, military applications, long-distance driving, and mining.

In essence, the digital mock pattern emerges as a potent ally in the pursuit of human-centric development, offering not only adaptability to varied scenarios but also the potential to enhance creativity and innovation in the design process.

Introduction

Software Engineering as Systems Engineering Specialized for Change

This section posits software engineering as "systems engineering specialized for change," asserting that repurposing established software engineering techniques for flexible and digital manufacturing systems yields both theoretical and practical insights. Unlike the conventional notion of development merely creating an artifact, this perspective delves into the deeper understanding of a system that is in constant construction and evolution. While software engineering is commonly associated with computer code, it fundamentally represents a form of systems engineering, where code is an outcome of the implementation process.

Software as Easy to Change

Renowned author Robert Martin describes software as "soft systems" that are inherently easy to change, distinguishing them from hardware systems, known for their resistance to change [1]. Turing's concept of computationally universal machines, being Turing complete and capable of constructing another Turing complete machine, emphasizes the inherent malleability of software. This perspective defines software as a system that is inherently easy to change.

Martin draws an analogy between performance and ease of change, highlighting the impracticality of a high-performance machine that lacks adaptability. This analogy underscores the importance of constructing modular, reusable, and generalizable "soft machines" on top of hard machines to facilitate change. This contrasts with application-specific machines, emphasizing the flexibility of software in contrast to traditional manufacturing tools.

Applying Software Engineering to Non-Computer Problems

The application of established software design patterns, such as the client-server design pattern, extends beyond traditional computing to non-computer problems, serving as versatile system design patterns. Taking the example of a take-out restaurant, these patterns not only provide a structure for problem-solving but also isolate changes, minimizing the impact of modifications. This adherence to design patterns aligns with SOLID principles [2], fostering positive effects on system design and development.

The figure that follows summarizes software as "easy-to-change" systems, illustrating how a software layer applies to computing, robotic, and manual assembly processes. Design patterns, as depicted, transcend code and serve as a vocabulary of standards, fostering effective communication, collaboration, and reuse.

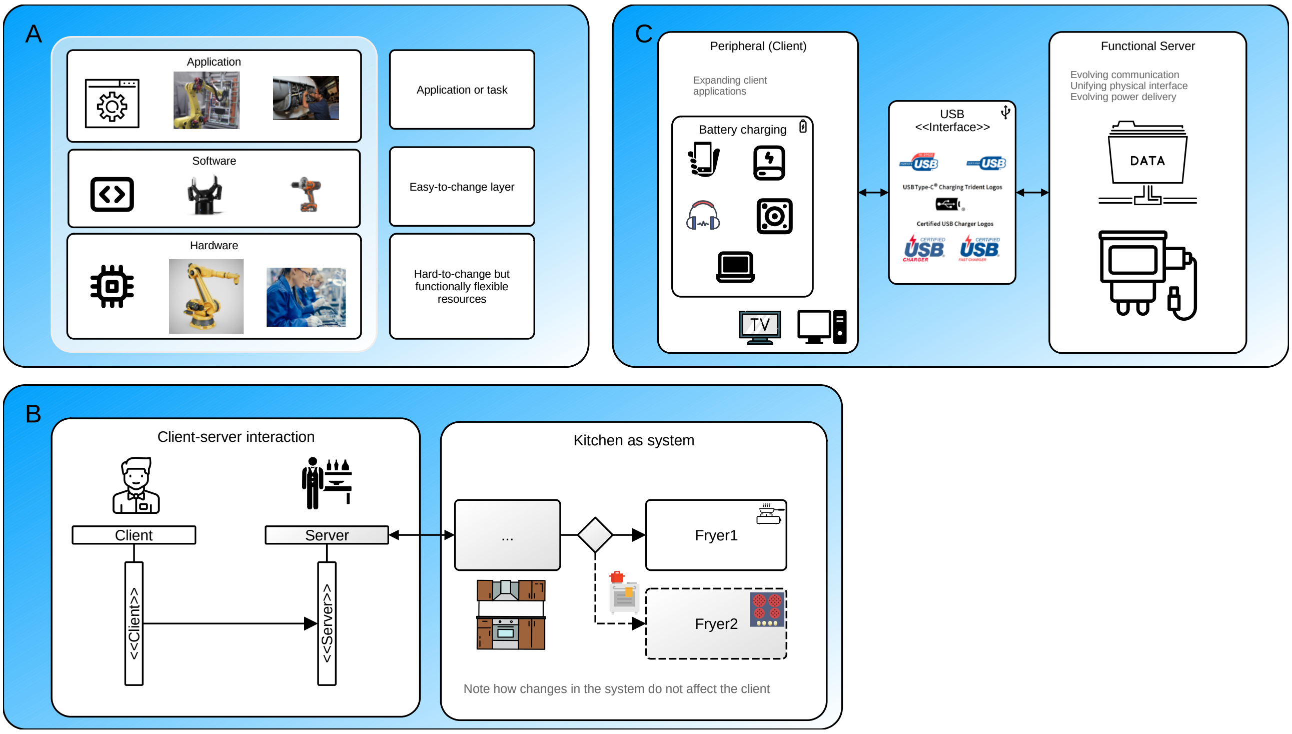


Figure x: Summary of software as “easy-to-change” systems. Having a software layer applies to computing, robotic, and manual assembly processes [A]. Design patterns apply to systems, not necessarily code [B]. USB is an example of how software can enable evolving systems [C].

Implications on Long-Term Applications

The ease of changing a system, as exemplified by software, holds profound implications for long-term applications. The USB standard serves as a prime example, unifying various functionalities such as battery charging, data communication, and backward compatibility. This approach reduces waste by promoting modular, reusable products, provides flexibility for system adaptation to new features, and enables the maintenance of legacy products.

Revisiting the Relationship Between Manufacturing and Software

While the relationship between manufacturing and software is not a novel concept, this work advocates revisiting it in the context of increased flexibility and digitization. Examples demonstrate how manufacturing systems can benefit from applying software engineering methodologies, emphasizing the utility of design patterns in offering reusable solutions and best practices while simplifying complex problem-solving.

Objectives

This work specializes an existing software design pattern to address the challenges posed by human operators.

Literature

Challenges in measuring human operators

Humans are significantly more difficult to measure than their machine counterparts. Firstly, because machines operate longer hours, we can gather more data from machines. We can easily have machine operators for 20 or more hour shifts, whereas doing the same for a human is simply unethical. These longer operating hours mean we can gather more data from machines over longer windows of time.

The second challenge is the effect of measuring. While retrofitting a machine with additional sensors presents no challenges, the same cannot be said for humans. Measuring operator's state, performance, and activities are invasive. While this may seem like a small issue that can be overcome with time, higher levels of stress are associated with a greater risk of injury and lower performance levels [3]. This poses the direct problem that measuring adversely affects the performance of operators, not revealing their true performance. In the case of wearable gloves and sensor-based instrumentation and tools, the cause is not psychological but physical. These gloves, tools, etc., directly interfere with the operator's agency, comfort, task familiarity, and ability to perform the given task. In the end, the act of measuring human operators can inhibit their performance, leading to biased data.

The third issue of ethical use of data is of growing concern. In general, there have been numerous scandals involving mega-corporations like Google, Facebook, and Amazon regarding the abuse of general users' data [4]. While Europe has regulated the storage location and uses of citizen data [5], they have also begun looking at the ethical use of data in the workforce [6], quoting the right to privacy [7]. Regulations inhibit the sharing of data between business entities and limit the application of data for hiring based on performance.

Challenges in modelling

Human behaviour modelling is a wicked problem from the point that “a change to resolve one aspect of the problem may create another problem”. The complexity of human models is caused by a few characteristics best juxtaposed with their machine counterparts.

Firstly, humans exhibit dynamic behaviour that can change rapidly over time due to states like learning and fatigue. Machine models, on the other hand, tend to operate under predefined rules and exhibit steady-state behaviour. This becomes obvious when we compare a 12-hour shift of industrial robot assembly with that of manual assembly. Human operators' performance is likely to suffer from reduced throughput and increased errors, while machine performance remains unchanged. Modelling the dynamic behaviour of humans is challenging and often requires real-time data.

Revealing the second issue, that human internal states like learning and fatigue are not directly measurable. This leads to estimation and observation of ill-defined quantities that can only be relatively defined. There is no absolute measure (ground truth) for internal states like fatigue and learning, making models relevant only within a small domain (limited transference). 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) and instrumentation (steering wheel and chairs) are good estimator of fatigue [8], [9]. Yet, it was observed that seasoned long distance drivers experiencing micro-sleeps stabilized steering wheels with their legs [10]. The fatigued well experienced driver exhibts the same behaviour as the well-rested inexperienced driver. Observing the internal state will increase the model transference and is essential for suggesting actions.

Repeatability of measurements are also an issue influenced by long-term learning, interindividual variability, and biological factors. These issues are suggestive of a probablistic model instead of a deterministic one, again make modelling challenging and may require additional data.

The approach recommended here

From this point of view, small changes to a workstation can result in vastly different behaviour. For this reason, regular validation is required. For example, [11] found a throughput rate valid for a range of complex tasks, while the quality risk model was valid for a subset of tasks. Let us distinguish validation from tuning, where a valid model describes the operator behaviour for a task or domain, and tuning parameters increase the accuracy of the model for the specific task. Hence, the HPM will need to be validated and tuned often enough that it should be included as a core component.

In order to address the challenges presented by measuring the operator, we suggest using the human performance model to observe the internal state. This is an open research question [12].

Digital mocking design pattern

Mocking design pattern

Mocking is well established design pattern that involves using a mock-model to test or develop a system component under specific considerations (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. This has several positive effects. (1) It enables prototyping, parallel development, and deferring implementation through modular component separation. For example, a single file database could be used during development, while a large online SQL database is being developed. Similarly, different DB vendors could be investigated for feasibility. (2) It enables testing the system under artificially constructed states. For example, the systems behaviour can be tested when the DB is empty or full.

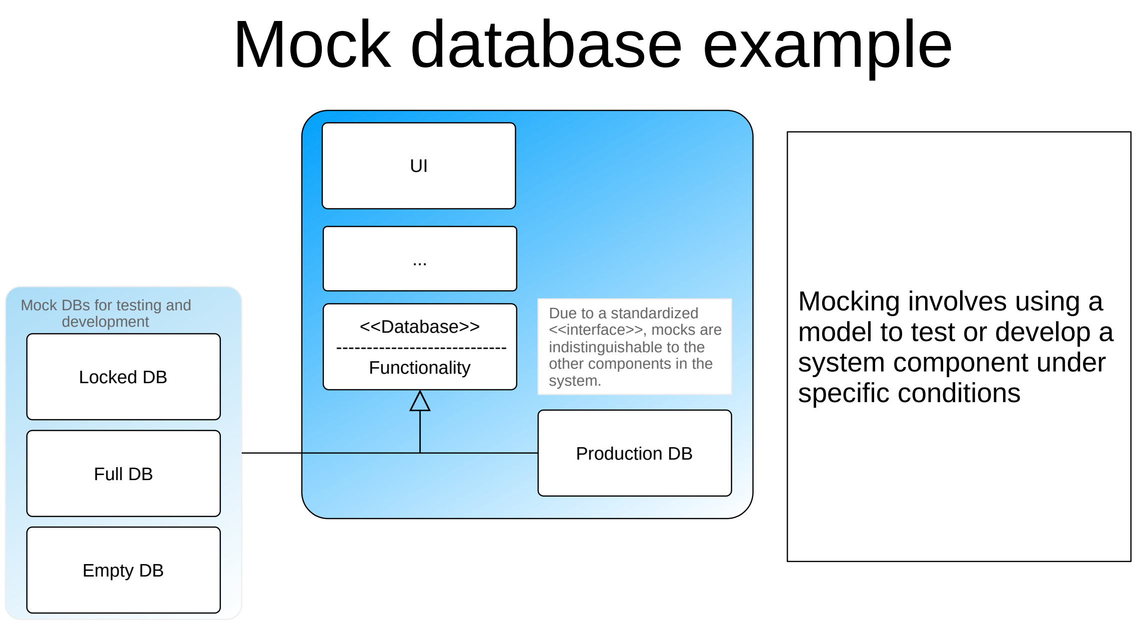


Figure x: The database (DB) example illustrates how different states of a DB are tested without modifying the production DB. This allows testing and development of an empty, full, or locked DB without disrupting production.

Components

The pattern needs to be adapted for human-centric systems, hence crucial modifications are made. Firstly, the virtual mock is introduced as a more concrete version specialized for human systems. In the case studies, we build a virtual reality version of the physical workstation with the intention of a substitutable mock. This substitution is later validated in a case study. Humans interact with the virtual workstation instead of the physical one. This facilitates the rapid prototyping of new systems, reconfiguration, and development while deferring the implementation of hardware systems. This virtual substitution is similar to the digital twin but requires virtual reality as an immersive digital substitution for the physical system.

Secondly, we introduce the human performance model. The human performance model predicts the operator outputs within a small domain. [13] suggests the digital twin as a high-fidelity model reflecting causality, and the digital shadow as a model reflecting statistics. This adequately describes the roles of the virtual workstation models and HPM and. Additionally, the HPM model is “cheap to compute” and serves as an abstract model, in contrast to the “high cost” HITL simulation.

Thirdly, a scheduler. The scheduler takes action based on the previous output from the workstation. This could be to rest, change tasks, etc. This is not apparent from a machine point of view, but human performance is dynamic. Additionally, we make the argument that dynamic human schedulers are control systems and a means of ensuring ethical work conditions through empathetic objective functions. These modifications allow the system enough flexibility to be adapted.

Case studies

From viewing the previous studies through the reference of this pattern we can summarize this investigation more accessibly.

Virtual validation

In the initial investigation, the suitability of the virtual workstation as a substitute for the physical one was tested by examining established and novel models. A series of tasks, simulating varying degrees of complexity in common assembly tasks, including random or repeatable tasks and sequentially dependent or independent tasks, were conducted. The assessment, depicted in Figure B and detailed in [14], aimed to determine if the virtual workstation could effectively replace the physical workstation. To this end, the virtual workstation performance was compared with established models.

1. The Wright learning model for task duration was valid for all tasks, but the model should be fit to each task.
2. The quality risk (index) of defective assembly was only valid for sequentially independent tasks. This illustrates why a validation step is required to establish whether the model holds in the applicable domain.
3. The dimensional assembly error was validated. This served as an illustration to quantify a measure that is not practically measurable in the physical world. Here the digital workstation is able to quantify a measure that is not practical in the physical world. Future works may explore this, acquiring information for which physical sensors are impractical.
4. The dynamic-gamma Wright learning model was proposed by enriching the previous model. This is an example of novel insights can be explored and the scale and fidelity of the data used to enrich this model was made practical by the ease of measuring in the virtual workstation.

These findings not only confirmed the virtual workstation's ability to simulate existing models but also highlighted its capacity to uncover novel insights.

Sample efficient human in the loop simulation

The subsequent investigation highlighted the significance of an intelligent scheduler. The Wright learning model, validated in the prior study, necessitated further tuning for specific tasks. This adjustment typically involves utilizing real-world data, supplied in this case by the virtual HITL workstation. Tuning the model parameters to the experiment proves costly due to the human labor associated with HITL simulation. Therefore, minimizing HITL labor would enhance the feasibility of this approach.

To address this, a sample-efficient scheduler was developed to reduce the number of trials, functioning as a Design of Experiments (DoE) module. It effectively blocked the effects of intra-subject experience and duration variability as noise. The reduction in experimental trials translated to decreased HITL labor for model tuning, exemplifying an empathetic objective function. In contrast, a function aiming to extract maximum data from operators would likely overburden them.

While this example is straightforward, it underscores the power and responsibility of the scheduler and its designer. Preserving operators' autonomy is crucial by allowing them to override schedulers. Additionally, human-centric schedulers should consider operators' internal emotional states, such as fatigue and learning, to ensure empathy. Caution is necessary to avoid dark patterns that may make free decisions possible but impractical, often through challenging paperwork or UI.

This development addresses a limitation in previous works, significantly increasing the scale of acquired experimental data. By combining the proposed adaptive online DoE with recent technological advances like on-device inference [14], low-cost VR, and previous findings such as remote databases and parallel DoE [15], [16], this data acquisition scale may facilitate further data-intensive applications and multi-location collaborations.

1. Reducing the number of human trials used to tune a model given a valid HPM.
2. Illustrating a feasible and empathetic objective function.
3. Employing the scheduler creatively.
4. Enabling a significant increase in experiment scalability.

This feature enhances the feasibility of HITL model tuning, significantly scaling up data collection. It is envisioned that this will encourage continuous improvement of workstations through digital prototyping.

Assembly design decision support framework

The concluding investigation demonstrates the practical application of a system constructed using the specified pattern to address contemporary challenges. This approach streamlines the selection of assembly designs by considering both printing costs and manual assembly expenses. Significantly, it enables a comparative analysis of artifacts within the system, such as different product assemblies, against external system elements like the costs associated with 3D printing. This aids in decision-making, with the HPM, scheduler, and Axiomatic design seamlessly integrated into the decision framework.

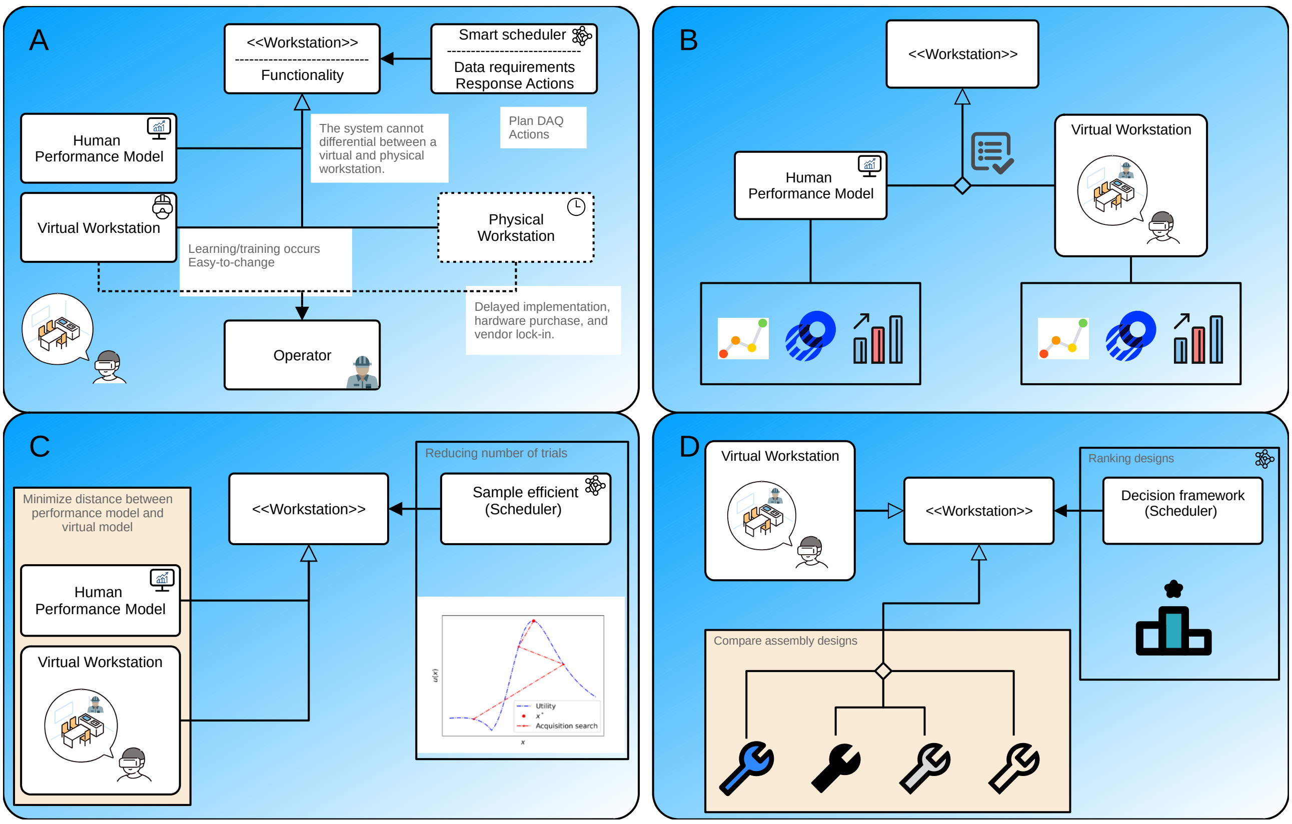
The virtual workstation assesses human performance for each assembly, while the quality of the assembly is gauged using an HPM to measure assembly dimension errors and assembly durations.

These measurements are subject to testing to confirm their adherence to specific distributions. The verification of the independence between assembly duration and assembly error is conducted through data obtained from the HITL simulation. However, it remains unclear whether this relationship holds universally and necessitates confirmation on a case-by-case basis.

In summary:

1. The HPM is quantified for each assembly.
2. Assumptions regarding the correlation between assembly time and assembly error are validated but need confirmation on a case-by-case basis.
3. Modeling assembly time and assembly error as gamma and log-normal distributions is validated.
4. The decision framework combines internal and external data sources, including tuned HPM, validation of assumptions, external data, and numerous designs.

Despite the various advantages of additive manufacturing, its manufacturing flexibility presents challenges in terms of design decisions. Integrating HITL simulation with decision support facilitates navigating these opportunities. It underscores the importance of a human-centric workstation capable of validating assumptions, tuning models, incorporating external information, and simulating changes to the workstation and work piece.



Research contributions

Through the digital mocking design pattern, we summarized on the case study studies. This section reflects on the contributions and implications on human-centric manufacturing system.

The wicked nature of modelling human behaviour has caused most of the manufacturing industry to pursue a black box approach. This has several non-obvious implications. Firstly, the opacity of black box models, does not offer suggestions on process improvement where a white box model reveals factors hindering performance. Secondly, big-datasets require constantly measuring operators, typically using wearable, yet the discomfort caused by these and the performance loss is not considered. Thirdly, big-data models have lots of system inertia and are not conducive to iterative design environments. This work, through case study implementations, show that perhaps an iterative approach specialized to human systems offers an alternative.

In the digital mocking pattern, the digital twin concept was specialized to human operators containing a HPM, a virtual workstation, and dynamic schedule controller.

It became clear that HPMs should be validated and tuned upon iteration.

Research contributions

Virtual Validation:

- The study validates the suitability of a virtual workstation as a substitute for a physical one through various assembly tasks of different complexities.
- Findings confirm the virtual workstation's ability to simulate existing models and quantify measures practically unmeasurable in the physical world, demonstrating its potential for uncovering novel insights.
- Introduction of the dynamic-gamma Wright learning model enriches existing models, showcasing the adaptability and scalability of the virtual workstation.

Sample Efficient Human in the Loop Simulation:

- Highlights the importance of an intelligent scheduler in the context of the validated Wright learning model.
- Develops a sample-efficient scheduler, functioning as a Design of Experiments (DoE) module, to minimize human-in-the-loop (HITL) labor for model tuning.
- Emphasizes the scheduler's role in preserving operators' autonomy and considering their emotional states to ensure empathy.
- Addresses a limitation in previous works by significantly increasing the scale of acquired experimental data, enhancing the feasibility of HITL model tuning.

Assembly Design Decision Support Framework:

- Demonstrates the practical application of the system constructed using the specified pattern to address contemporary challenges in assembly design.
- Streamlines assembly design selection by considering both printing costs and manual assembly expenses.
- Integrates Human Performance Model (HPM), scheduler, and Axiomatic design into the decision framework for a comprehensive analysis.
- Validates assumptions regarding the correlation between assembly time and error and models assembly time and error as gamma and log-normal distributions.

Overall Contributions:

- Envisions continuous improvement of workstations through digital prototyping.
- Addresses challenges in additive manufacturing design decisions through the integration of HITL simulation and decision support.
- Underscores the importance of a human-centric workstation capable of validating assumptions, tuning models, incorporating external information, and simulating changes to enhance decision-making.

In summary, the contributions encompass advancements in virtual validation, efficient human-in-the-loop simulation, and a practical decision support framework for assembly design, showcasing the potential of the proposed pattern in addressing real-world challenges in human-centric systems.

Limitations and future research

One advantage inherent in the Design Science Research approach lies in the development of theory within the specific context of the system. This encourages iteration to constantly improve performance.

The validation of the Wright learning model across all tasks served as a catalyst for elevating the model's status from deterministic to probabilistic. To enhance this model further, future investigations should explore the fitting of learning parameters based on predetermined factors such as operator experience, fatigue, task duration, and the number of components. This would deepen our understanding of the interaction between operator learning and task complexity, reducing our reliance on virtual HITL tuning.

On the other hand, limitations in the task applicability of the quality risk model to sequentially independent tasks revealed a significant knowledge gap that merits a mechanistic investigation. An innovative approach would incorporate a multi-model HPMs [17] to selects the appropriate white-box model, combining the advantages of precise predictions with insightful suggestions for improvement.

Acknowledging the assumed non-critical concern for system performance, future work could explore more established methods like Gaussian Process Regression for improved sample efficiency in the Design of Experiments (DoE) method. Similarly, the sample-efficient dynamic scheduler could be specialized for swift differentiation of human performance in small workstation changes, significantly enhancing the feasibility of virtual HITL iterative improvement methods.

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