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A simulation-based decision-support system for integration of human cognition into construction operation planning

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Abstract

The mental workload associated with work activities is a key factor affecting the performance of human resources in labor-intensive construction operations, in turn impacting work behavior. While most accidents in construction are caused by unsafe behavior, modeling behavior in construction projects remains challenging and relatively unexplored. Here, human cognition is incorporated into the design of construction operations to analyze the mental task demands associated with various designs. A framework that integrates cognitive modeling with a simulation-based decision-support system capable of analyzing existing and non-existing operations in a simple and automated manner is proposed. The superiority of the proposed framework is that it eliminates the need for prior knowledge of the underlying cognitive theories. Functionality of the developed framework was evaluated following its application to a case study of welding operations, where the proposed method was shown to successfully evaluate the trade-off between mental workload and productivity for different operation scenarios.

Keywords: Human cognition; mental workload; simulation modeling; construction safety

1. Introduction

By directly impacting safety and productivity of operations, human resources have a crucial role in the success of labor-intensive construction projects (El-Gohary and Aziz, 2013; Golabchi et al., 2018). A primary contributor to human performance and behavior is the mental workload associated with work activities, as it impacts decision-making behavior (Khosravi et al., 2013). However, modeling decision-making behavior that impacts work performance, particularly in the areas of safety and productivity, is challenging and must be further explored.

Despite numerous studies attempting to improve construction safety, accident rates in the construction sector remain one of the highest among major industries (Choi et al., 2011). Unsafe work behavior continues to be identified as a leading cause of construction job site accidents (Fang et al., 2016). The traditional approach to safety management (i.e., the normative paradigm) focuses on compliance with safety regulations and ignores the impact of production system features on work behavior. As a result, the impact of behavior on errors, accidents, and performance is regularly overlooked (Mitropoulos et al., 2009). Accordingly, a new approach that considers the impact of production factors and task features on work behavior and unsafe acts is needed. Since production factors impact work behavior through mental workload (Mitropoulos and Memarian, 2013), such an approach must incorporate mental workload into the design and planning of operations to mitigate or prevent unsafe and unproductive behaviors (DiDomenico and Nussbaum, 2011).

Cognitive modeling has the potential to reliably model decision-making behavior through the evaluation of workers' mental states. Construction tasks involve substantial mental demands (DiDomenico and Nussbaum, 2008; Mitropoulos and Memarian 2013), and analyzing these demands is necessary to predict how workers' cognitive states will affect their work behavior. For instance, high-task demands that cause overload, low-task demands that cause underload, mental fatigue, monotony, and reduced vigilance (Nachreiner, 1995) can all lead to decreased performance and safety. Since cognitive modeling deals with the characteristics of a work environment and its impact on human behavior (Rasmussen et al., 1994), it can be incorporated into the design of construction operations to identify undesired task demands (i.e., higher or lower than acceptable thresholds) that result in decreased safety and performance.

Existing methods for incorporating human cognition into the design of labor-intensive construction operations are limited by the requirement of practitioners to have prior knowledge of the underlying cognitive theories to effectively leverage the benefits of these method. In contrast, this study has developed a decision-support system (DSS) where cognitive modeling is integrated into construction operation planning. To this end, a simulation-based DSS, which enables a simple, automated modeling and analysis of existing or non-existing operations without requiring extensive knowledge of cognitive models, is proposed. Here, the simulation component enables evaluation of various scenarios, which allows practitioners to evaluate the trade-off between mental workload and productivity for different operation plans. Using these results, practitioners can determine which scenario is most efficient from the perspectives of both safety and productivity.

The next sections describe the research background and the methodology for developing the DSS. Then, implementation of the developed DSS in a case study of welding operations is demonstrated. Finally, the discussion and conclusions are presented.

2. Research background

Despite substantial efforts to improve safety in the construction industry, the rates of accidents, injuries, and fatalities remain high (BLS, 2018; OSHA, 2018; Socias-Morales et al., 2018). Previous studies have shown that unsafe behavior is a leading cause of most construction job site accidents (Fang et al., 2016; Bohm and Harris, 2010; Haslam et al., 2005; Suraji et al., 2001). Many conventional approaches have focused on compliance with safety rules and regulations. However, they often fail to consider how (1) characteristics of the production system impact work behaviors and affect the potential for errors (Mitropoulos et al., 2009) and (2) the influence of work practices and procedures impact work behavior (Cupido, 2009). Accordingly, unsafe behaviors must be prevented by eliminating root causes and reducing the potential for unsafe acts through the intentional design of construction operations.

2.1. Mental workload and cognitive modeling

One of the main contributors to unsafe behavior is the amount of mental workload associated with a task (Khosravi et al., 2013). Mental workload, which is a function of an individual's cognitive capacity as well as task demand, can be defined as the ratio of mental resources required to carry out an activity compared to the total mental resources available (Carswell et al., 2005). Both high and low workloads have been shown to result in decreased performance, increased errors, and additional unsafe acts (Mitropoulos and Memarian, 2013). Since construction operations involve substantial mental demands (DiDomenico and Nussbaum, 2008; Mitropoulos and Memarian, 2013), understanding and analyzing cognitive task demand is critical for predicting the cognitive performance of operators and improving worker performance. Tasks that cause overload and underload can be mitigated or avoided by using cognitive modeling to evaluate demands and (re)design operations.

Cognitive theories have been primarily developed and applied to other sectors, such as the aviation (Seamster and Redding, 2017), transportation (Recarte and Nunes, 2003), and power plant (Boy and Schmitt 2013) industries. The construction industry can also benefit from applying human cognition to design operations (Saurin et al., 2008; Mitropoulos et al., 2009). A few studies have explored the use of cognitive modeling and cognitive systems engineering in construction. For example, Fang et al. (2016) developed a cognitive model of construction workers' unsafe behavior to represent workers' cognitive processes when facing potential hazards. Dadi et al. (2014) investigated the cognitive workload demand of different engineering information formats. Mitropoulos and Memarian (2013) explored task demands of masonry work and its impact on performance. Saurin et al. (2008) showed how some important safety management practices (e.g., safety planning, proactive performance measurements, identification and monitoring of pressures, etc.) can be improved based on cognitive systems engineering principles. These studies demonstrate the benefits of applying cognition research to construction operation planning to improve safety. However, research in human cognition and its application in the industry is still in its infancy (Fang et al., 2016; Dadi et al., 2014; Mitropoulos et al., 2009; Saurin et al., 2008). Unlike physical demands, most construction safety studies have not considered cognitive issues, such as mental workload and task demands, resulting from work scenarios and the environment (Saurin et al., 2008). Thus, a systematic approach for evaluating construction task demands is required to understand and prevent unsafe behavior and errors (Mitropoulos and Memarian, 2013). This study intends to provide such systematic means for designing construction operations by understanding how the process design impacts workers' mental workloads and, consequently, increases the likelihood of accidents.

2.2. Productivity versus safety

Since safety performance is highly correlated to productivity (Hallowell, 2011), one of the main concerns in construction practice is the ongoing tension between safety and productivity in the workplace (Mitropoulos et al., 2009). Production demand directly impacts safety performance through work pressures that result in hazardous situations and adversely affect work behavior, thereby increasing the likelihood of accidents (Mitropoulos and Cupido, 2009; Mitropoulos et al., 2009; Goldenhar et al., 2003). Thus, because of production pressures, improvements made to safety through new work methods tend to be ineffective due to negative impacts on task demands and mental workload (Mitropoulos et al., 2009).

Understanding the impact of work practices on task demands and the likelihood of errors and accidents is crucial to ensure safe and productive operations (Mitropoulos et al., 2009). Work design and planning must incorporate the evaluation of task demands and mental workload to identify tasks that encompass higher likelihoods of errors (Mitropoulos and Memarian, 2013). This study proposes an approach to analyze the relationship between productivity and safety by simultaneously evaluating the impact of work design on mental workload and performance. Thus, this approach enables modeling of workplaces and operations that decrease the likelihood of errors and accidents while improving productivity.

2.3. Integrating cognitive modeling into simulation-based DSS

DSSs have evolved as computer-based tools that facilitate analysis and decision-making for construction operations. With a DSS, users can analyze various scenarios and make more informed decisions by integrating data with analytical and heuristic models (Chau et al., 2003; Leu et al., 2000). DSSs have been shown to be effective for modeling various aspects of construction operations, such as project management (Zavadskas et al., 2012), prefabrication (Hwang et al., 2018), infrastructure management (Park and Kim, 2013), safety monitoring (Cheng and Ko, 2002), and safety planning (Kim et al., 2018), with the aim of improving productivity and safety in construction (Mahfouz, 2012; Cho and Hastak, 2012; Tam et al., 2002). Despite the effectiveness of DSSs in improving productivity and safety through better decision-making, the impact of human cognition has often been overlooked in construction operation planning (Saurin et al., 2008).

Leveraging DSSs for designing work systems and production practices during the planning phase—before workers are exposed to demanding operations—can facilitate decision-making and reduce complexity and uncertainty of operations. Simulation modeling can represent characteristics of the work system and its elements in a manageable scale to observe the feasibility of different work scenarios. Furthermore, simulation modeling is a highly effective tool to analyze and plan for productivity (Dozzi and AbouRizk, 1993). In particular, a simulation-based DSS can be effective to model human cognition and workload demands due to the harmony between simulation and cognitive modeling. Cognitive modeling focuses on the how a work system impacts decision-making, work behaviors, and likelihood of errors (Mitropoulos et al., 2009), where such errors indicate the existence of an issue within the work system (Dekker, 2006). Thus, integrating cognition and simulation enables analyzing work systems in terms of mental workload and productivity, and provides insight into how the design of work systems can reduce the likelihood of errors and accidents.

3. Methodology

A DSS framework that incorporates human cognition into simulation modeling to evaluate the mental workload and productivity of labor-intensive construction operations, while concurrently planning safe and efficient operations, is proposed. The structure of the framework and a flowchart of the decision-making process is illustrated in Figure 1. First, as shown in Figure 1, a work operation design that represents either an existing or non-existing operation is analyzed to identify characteristics, such as sequence and duration of activities or required resources. Then, the analyzed information is used to evaluate the design based on cognitive models to determine the corresponding task demand and cognitive state of the operator. The cognitive model is detailed in Section 3.1. The results of this evaluation are then used to determine if the obtained mental workload levels fall within acceptable thresholds. These thresholds are identified based on the cognitive model used. In this study, the Cognitive Task Load (CTL) model was adopted as a cognitive model; the thresholds of this model are illustrated in Figure 2 and described in Section 3.1. Finally, the operator's productivity performance (measured by duration of operations) and safety (measured through mental workload state) are obtained using the simulation model. A special purpose simulation tool was developed to capture this information. Details of the developed simulation tool are provided in Section 3.2. This information can then be used to redesign the operation or evaluate different scenarios to achieve an optimum design through experimental scenario analysis using simulation. Implementation of the framework in a case study is demonstrated in Section 4.

3.1. Cognitive task load model

To evaluate the mental workload associated with manual tasks, different methods have been developed, including subjective and objective methods. Subjective methods involve assessing the operator's judgment of the operation's cognitive workload (Reid and Nygren, 1988). While these methods are appropriate for overall ratings, they are not suitable at a detailed work level, as operator biases may decrease accuracy of the outputs (Moray, 2013). Rather, these techniques are best suited for existing operations and are limited for analyzing operations that do not currently exist. Consequently, objective methods are more suitable for the purposes of this study.

The Cognitive Task Load (CTL) model (Neerincx, 2003) was adopted for this study, as it provides an effective method to evaluate mental workload of activities without requiring operator feedback. The CTL model evaluates task demands and identifies associated cognitive issues (e.g., cognitive lock-up resulting from excessive workload or lower vigilance resulting from highly-repetitive tasks) (Colin et al., 2012). As a result, the impact of a work system and task design on operator performance and mental effort can be evaluated. The CTL model classifies an operation by three attributes that evaluate the operator's cognitive state:

1. *Time occupied* (TO), which is the ratio between the time it takes the operator to carry out a task and the total time;
2. *Task set switches* (TSS), which is the number of times that the operator switches between tasks; and
3. *Level of information processing* (LIP), which adapts Rasmussen's skills-rules-knowledge model of human performance (Rasmussen, 1983).

After acquiring the values for the TO, TSS, and LIP variables, the mental state of the operator is obtained through the cube model representation shown in Figure 2. The transparent areas of the cube are acceptable regions, and the solid areas represent cognitive issues that can impact the operator's performance and safety. Based on the resulting mental state returned by the CTL model, interventions are taken (e.g., modifying design) to address the identified cognitive issue.

This study incorporates the CTL model into a simulation modeling environment, and the TO and TSS variables are obtained automatically through the model without manual input. Furthermore, the calculated mental workload of the operation automatically updates the rest of the simulation model and provides more reliable results in terms of operator efficiency and overall productivity. By integrating the CTL model with simulation, construction practitioners can model tasks and operations and obtain the mental workload of their design without requiring prior knowledge of the CTL model or the principles of human cognition theories.

3.2. Special Purpose Simulation for Human Cognition Modeling

The *Simphony* (Hajjar and AbouRizk, 1996) modeling environment is used to integrate the CTL model with simulation. The *Simphony* environment provides a structured approach to Special Purpose Simulation (SPS) modeling. As a result of SPS modeling, precise simulation modeling can be carried out with less time and effort compared to general-purpose simulation, due to decreased complexity and abstraction (Chua and Li, 2002). An SPS tool that uses the CTL model as part of the simulation to provide feedback on the mental state of the operator was developed. The template includes a composite element, task element, and idle element. The modeling elements with their inputs and outputs are described in Table 1, along with an example of the interface in Figure 3. As shown in Figure 3, the composite element represents an operation that includes a sequence of tasks (e.g., one full cycle of an operation). These composite elements for different operations connect to each other to represent an operator's entire working shift or can be used as part of a larger simulation model of a construction process. The task elements inside a composite element represent the individual tasks that an operator carries out to complete the operation. LIP and task duration are inputs into the task element, while the idle element only has duration as its input. These elements can also be used in conjunction with any simulation model created using the general template in *Simphony*. After running the model, the cognitive load of each operation is calculated at the operation level and presented as an output, along with the total duration of manual tasks; idle times; and average LIP, TO, and TSS.

4. Case study

To evaluate functionality, the framework was implemented to model a steel welding operation. The welding operation was selected, as it represents one of the most critical and labor-intensive jobs on many construction sites in terms of productivity and safety. In a welding operation, a welder carries out various activities (fitting, grinding, measuring, welding) that require considerable mental effort. Thus, the welder's cognitive state is important and typically has a direct impact on the success of the overall operation. The framework was adapted to model and evaluate the cognition load of the operator during the existing welding operations (i.e., base scenario), as well as to analyze different scenarios of the operation to find the best in terms of both productivity and mental workload. The welder's tasks during a welding cycle include reviewing blueprints, making measurements, marking the steel beam, carrying steel plates, placing plates in designated spots, grinding the plates, and welding plates to the beam. In the case study, the welder welds six plates to a steel beam during the modeled operation; Figure 5 shows the welding workstation.

The existing welding operation was modeled as the base scenario. To model the base scenario in the simulation environment, a full cycle of the operation was observed and videotaped. The video recording was used to extract the duration of different tasks and to model them accordingly.

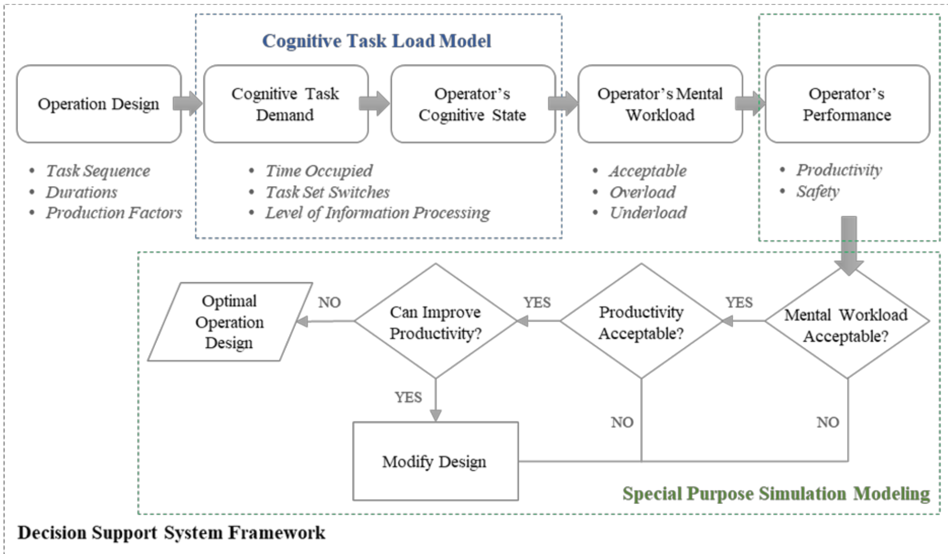


Figure 1. Framework of simulation-based DSS for human cognition.

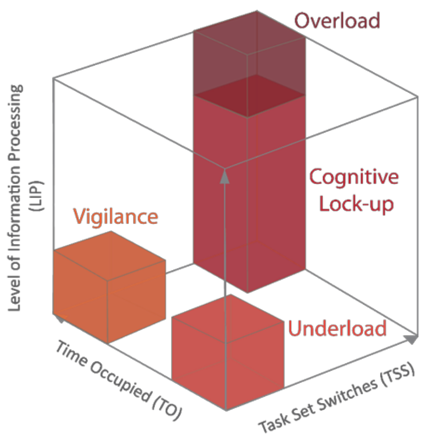


Figure 2. 3D representation of the cognitive load space of the CTL model (adapted from Neerincx, 2003).

During the base scenario, the welder first reviewed the blueprints to understand the location and orientation of each plate and then marked the beam accordingly. This process of reviewing the blueprint and marking the beam was repeated six times (once for each plate). The welder then moved the plates to spread them out on the beam and ground them. Then, they moved each plate into its appropriate location on the beam, carried out the measurements, marked the beam, and repeated this process for all of the plates. Finally, the welder hammered each plate to fix it into the exact location, performed the final measurements, and welded the plates. This cycle was also repeated six times.

The result from the simulation model for the base scenario is presented in Table 2. The simulation model outputs the duration of the operation, the corresponding LIP, TO, and TSS for the entire cycle, and the overall cognition load. The output enables planning for other scenarios that address existing cognition issues while also evaluating the efficiency of each. As shown in Table 2, the base scenario results in a cognition overload. Thus, other scenarios must be modeled and analyzed to address this mental state. Figure 6 shows the process of designing different potential scenarios.

To address the mental overload observed in the base scenario, the model was modified to incorporate more rest (idle time) and to reduce the level of information processing required, as shown in Figure 6. These changes to the base scenario resulted in a cognitive state of underload while increasing the duration of the operation (Scenario 1). For the next scenario (Scenario 2), the given rest time was reduced, resulting in a cognitive state of vigilance. For Scenario 3, the amount of time spent on low LIP tasks was reduced, which resulted in a state of cognitive lock-up. Returning the rest time to the base scenario resulted in an acceptable cognitive state, but also a longer duration, which implies lower productivity (Scenario 4). However, the simulation environment enabled the restructuring of tasks to achieve an acceptable cognitive state and potentially improve productivity (Scenario 6). Figure 7 shows modifications in the design of the operation to achieve an acceptable cognition load and higher productivity. The scenario of adding another worker to assist the welder was also modeled and analyzed (Scenario 5), which resulted in acceptable cognitive state for the welder, but cognitive underload for the helper. Modeling availability of the resources and the new arrangement of the entire operation for both workers is also an important factor in practice, which is possible through the simulation modeling of the welding operation as part of the entire operation. The outputs of each scenario are summarized in Table 2 and visualized in Figure 8.

5. Discussion

The results of the case study demonstrate that the proposed integration of cognitive modeling into simulation-based DSSs can provide an effective means of modeling construction operations for safety and productivity analysis. Through the framework, the mental effort required, as well as the efficiency, of manual tasks can be more easily evaluated.

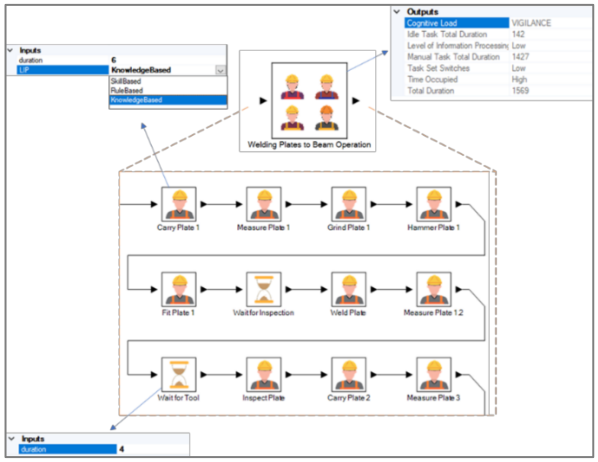


Figure 3. Example model representing the interface of the SPS template.

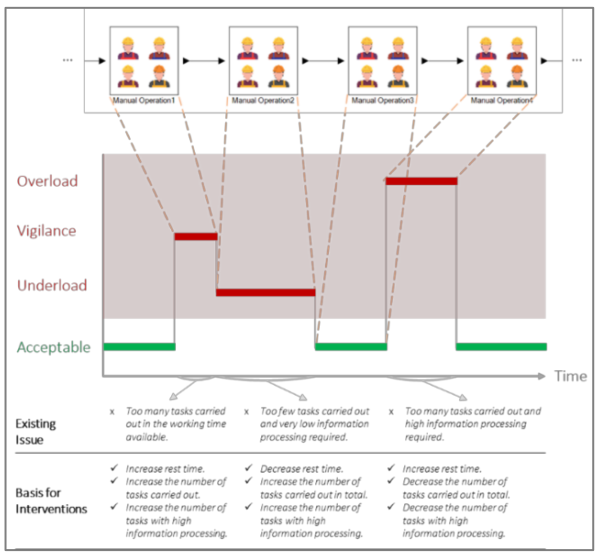
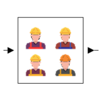


Figure 4. Mental workload, potential issues, and possible interventions for an operator's work schedule.

Table 1. Modeling elements of the developed SPS template.

Modeling Element	Interface	Description	Input	Output
Manual Operation		Represents an operation and contains a series of tasks. The cognitive load is calculated at this level.	• A sequence of manual tasks	• Cognitive load • Total duration • Average LIP • Average TO • Average TSS
Manual Task		Represents a single task with a specified duration.	• Duration • LIP	• Total manual task duration
Idle		Represents the time the operator is idle.	• Duration	• Total idle time duration

The following are some implications from the study:

(1) The cognition load output from the simulation not only provides feedback on the mental effort required to carry out a manual task, but also serves as a basis to modify the design of the operation and evaluate the impact of these modifications on the worker's mental state. In particular, the integrated simulation modeling component enables design and planning of operations and provides information on the productivity of various work methods. As shown in Figure 7, the simulation model can be a valuable tool to modify the design of an operation and evaluate the impact of the modifications. Accordingly, an output, such as Figure 8, can be achieved, allowing for the selection of the design with the highest productivity (i.e., lowest duration) and the most desirable level of mental effort required. In the welding operation of the case study, the mental effort required for the task is changed from cognitive overload to acceptable, and productivity is also increased by approximately 18%, as

shown in Table 2. The developed approach, therefore, integrates safety and productivity analysis and provides a new method for evaluating the correlation between both. It also enables the identification of production practices that decrease the likelihood of accidents while simultaneously improving productivity, thereby overcoming an existing challenge for construction researchers and practitioners (Cupido, 2009).

(2) The proposed approach was implemented on an existing labor-intensive operation (i.e., welding) as a case study to illustrate its application and effectiveness. However, the cognition-based simulation framework can be beneficial for modeling non-existing manual tasks (during the design phase), where limited information is available. Such an approach leverages the strength of simulation-based DSSs in allowing users to study various work situations that do not yet exist or are too difficult or expensive to manipulate (Shannon, 1998) without requiring previous knowledge of the underlying cognitive models. The results can justify the need for design adjustments to management by highlighting the impact of the changes on productivity—always a critical concern when applying new improvements for worker health and safety (Mitropoulos and Cupido, 2009). As future work, this framework could be incorporated into simulation-based modeling of a Predetermined Motion Time System (PMTS) (Golabchi et al., 2016). Through integration with PMTSs, the model would only require a description of the manual process to be evaluated, allowing users to model any task without prior knowledge of cognitive models, PMTS, or duration of each work activity. In such a case, the LIP variable would also be obtained automatically through the simulation engine based on the motion type, and expert judgement would not be required during the modeling process.

(3) While previous studies have indicated that designing operations that create high mental workloads should be avoided as much as possible, it is unrealistic to expect design professionals to understand the impact of their design on cognitive task demands (Mitropoulos and Memarian, 2013). The approach of this study addresses such concerns by providing feedback on the operator's cognitive state during the design phase, which provides design professionals with insight into the impacts of their design on safety and productivity.

Figure 5. Welding workstation.

Table 2. Result of modeling different scenarios of welding operation.

Scenario		Duration (s)	LIP	TO	TSS	Cognition
Base Scenario		1189	High	High	High	OVERLOAD
Scenario 1		1927	Low	Low	Low	UNDERLOAD
Scenario 2		1427	Low	High	Low	VIGILANCE
Scenario 3		1327	Low	High	High	COGNITIVE LOCK-UP
Scenario 4		1319	High	Low	High	ACCEPTABLE
Scenario 5	Welder	1235	High	Low	High	ACCEPTABLE
	Helper	264	Low	Low	Low	UNDERLOAD
Scenario 6		976	High	High	Low	ACCEPTABLE

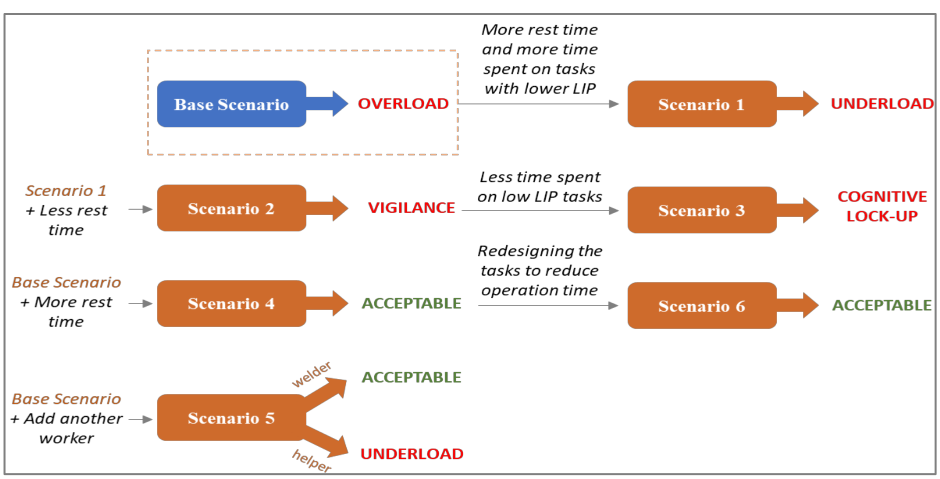


Figure 6. Strategy of modeling different scenarios of welding operation.

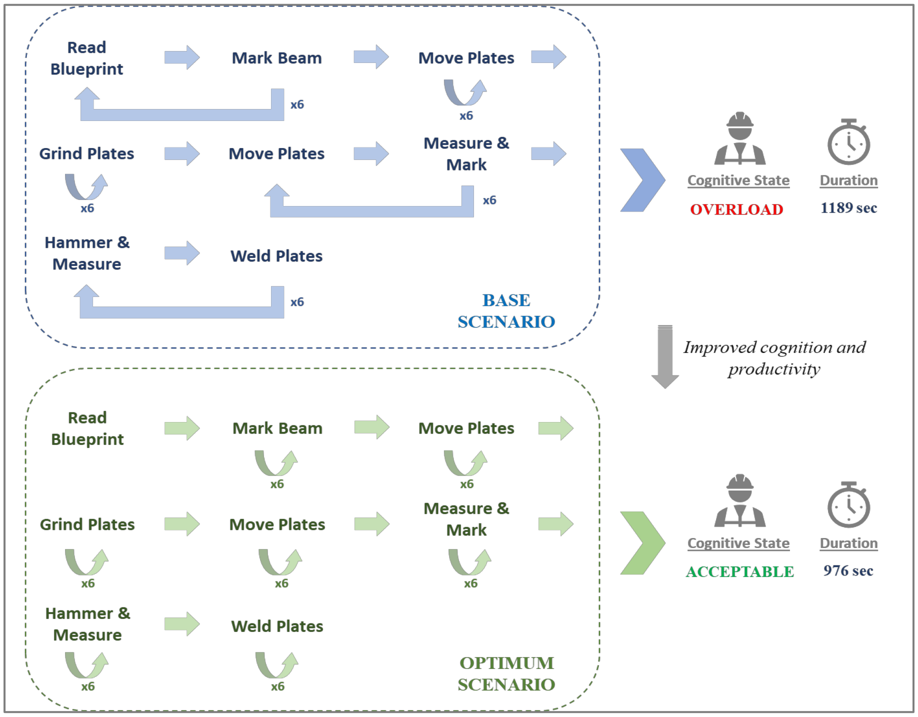


Figure 7. Comparison of base scenario and optimized scenario of the welding operation (Scenario 6).

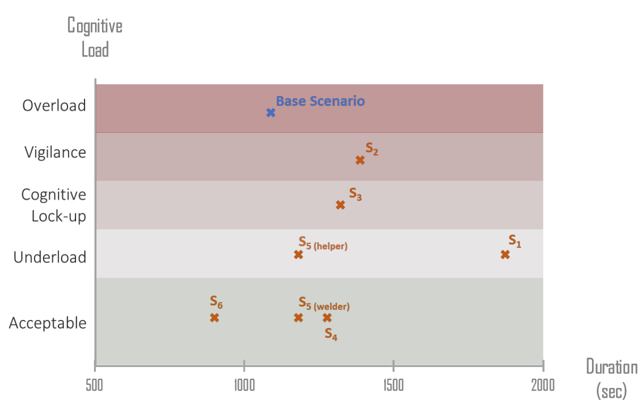


Figure 8. Comparison of different scenarios in terms of duration and cognitive load

(4) This study used the CTL model to analyze the cognition load of manual tasks as an example of a simple, effective model, and validated it for operators in dynamic, high-demand work environments (Neerincx et al., 2009; Colin et al., 2012). More research is required to identify and develop cognition models that can accurately simulate construction activities that have varying degrees of repetitiveness and physical demand. Once identified, these models should be integrated into simulation models for construction planning.

6. Conclusions

This study proposes a framework for a simulation-based decision-support system that integrates cognitive modeling into the design and planning of labor-intensive construction operations, thereby enabling the concurrent analysis of operations for both mental workload and productivity. The results from a welding operation indicate that an 18% increase in productivity can be obtained, while also mitigating the mental workload from a state of overload to within acceptable thresholds. The contributions of this study include: (1) providing a systematic approach to model and understand the impact of construction operation design and planning on mental workload; (2) proposing a simulation-based method for modeling mental task demands in an automated manner and without extensive expert knowledge; and (3) developing a framework to identify production factors and work practices that simultaneously improve safety while achieving high productivity. Using the proposed approach, construction practitioners can develop plans aimed at improving construction safety and productivity of workers during the early stage of a project—even as early as the pre-construction stage. A limitation of the proposed approach is the need to manually adjust the operation plan to achieve an optimal design. Directions for future work include evaluating approaches to automate adjustments to the simulation model, incorporating PMTSs into the framework to improve the productivity analysis of non-existing operations, evaluating the suitability of different cognitive models for analyzing construction tasks, and assessing the framework by modeling more complicated tasks.

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