



THE EXPERT LOCOMOTIVE ENGINEER'S MENTAL MODEL

SUMMARY

Researchers from General Electric (GE) Research and the Massachusetts Institute of Technology (MIT) Human Systems Lab are studying ways to improve the man-machine interface for the locomotive driving task and train handling with the assistance of advanced automation. This man-machine collaborative approach to the design of automated control systems promises improved locomotive control for both experienced engineers and those new to the job. The system design approach is to build-in and take advantage of expert drivers' knowledge and skills and the machine's ability to execute instructions more precisely than the engineer to provide better overall safety and efficiency. From October 2019 to July 2020, the team conducted the experiments at the Federal Railroad Administration's (FRA) Cab Technology Integration Lab (CTIL) (Figure 1). These experiments put expert and novice drivers in the simulated cab, allowing each to drive while blocking the view out the window from the driver (i.e., forcing interaction with the non-driving participant) and recording their interactions for analysis.

BACKGROUND

Automated systems for locomotives must be comprehensible and intuitive. To achieve the research goals, researchers recognized that the expert engineer's mental model of how to drive the train needed to be sufficiently well understood, thus motivating Price (2020) and its results as a necessary precursor for the GE study to prototype an enhanced automated control system.

For example, the ability to communicate an upcoming signal status to the engineer or in-cab

automation means that both the human and the automation can adapt to situations as they evolve, allowing for more flexible control modes. New safety challenges have spurred interest in the development of operating modes and automated driver aids that increase both safety and efficiency without diminishing the engineer's skills.

OBJECTIVES

Price (2020) describes the early stages of research for developing a shared control model for freight rail where the engineer can continually adjust the goals of the automated system to achieve safe and efficient management of the train's movement. For a shared control mode to be effective, the engineer would need a functional mental model of the automation—that is, the ability to understand and predict the behavior of the automation (for example, how it may change the speed of the train) given the engineer's inputs. This could be more readily achieved if the design of the enhanced automation was to behave in a manner that reflected the intentions and goals of the human engineer. In other words, building recognizable expert driving strategy and mental models into the automation facilitates a shared understanding of the world between the operator and the automation.

METHODS

The objective of the experiment was to identify the external factors, such as environmental cues, that are part of the engineer's mental model and control strategies when driving a route. Unlike other methods that treat tasks as independent of the overall context, both spatial and temporal position are important for analysis



of the engineer’s mental model. This study paired volunteer expert freight engineers with novice subjects with very little knowledge of rail operations as the operating crew of a freight train. The subject pair drove two routes together in the CTIL simulator (see Figure 1): one with the novice operator controlling the train (NAC, or “novice-at-the-controls”) and the other with the expert engineer controlling the train (EAC, or “expert-at-the-controls”). The participant operating the train controls was unable to see the external environment, thus participants had to orally communicate necessary information to enable an appropriate control action.



Figure 1. The right side of the CTIL, where the engineer typically sits

From the NAC scenario, the expectation was that the expert engineer, through their inquiries and instructions to the novice operator, would reveal the cognitive processes underlying key driving decisions, e.g., what information cued the decision, and how using the information led to a decision. In the EAC scenario, the expectation was that the content and timing of the information requests from the expert engineer would illuminate both the information engineers rely on for decision-making processes and the frequency at which they updated their mental models. Five expert/novice pairs drove the route, in addition to one expert/novice pair that participated in a pilot study that allowed the research team to refine the study methods. After each experiment, every interaction between the two subjects was coded using linguistic markup

by the type of interaction and its context, where Level 1 codes roughly corresponded to syntactic information, and Level 2 codes to semantics. Interactions were then analyzed, along with train handling data, to discern driving strategies and common elements of the mental model and control strategies.

Table 1. Sub codes used in linguistic markup to annotate domain-specific content of each interaction.

| Controls | Displays | Track | Train |
|---------------|-----------------------------------|-------------------|--------------------------------|
| Air brake | TO Display | Turn out | Speed |
| Dynamic brake | Accelerometer | Curve | Train type |
| Throttle | Counter-Distance Measuring Device | Grades | Slack action |
| Notch | | Switch | Train forces |
| | | Mile post | Train forces |
| | | Speed flags | Train breakage |
| | | Speed restriction | Front, end, or middle of train |
| | | Track speed limit | |

RESULTS

While space constraints prohibit detailed analysis here, some of the analysis results included (for EAC):

- Before conducting the experiment, researchers hypothesized that the frequency of query codes would serve as a proxy for the frequency with which an expert subject updated his or her mental model. However, the observed frequency was too low, possibly because the expert subject had access to external information most notably the modified track chart, to use the query codes frequency as a heuristic.
- For semantic (“Level 2”) codes, “check precondition” (CKP), which implies a particular planned action is in mind if the precondition exists, was by far the most



common code, at 68 percent of all interactions with a Level 2 label. This might include environmental cues, train status, or information from paperwork; the complete list of sub codes in [Table 1](#) illustrates possible subjects of these checks.

- The next most frequent codes were “clarify plan” (CLF), “confirm plan” (CNF), and “explain plan” (EXP), with 9, 9, and 8 percent of Level 2 codes, respectively. Plan-level actions are generally concerned with determining what to do if something occurs and when. As with the NAC scenario, the high frequency of “check precondition” codes indicated that the expert subject was generally following a predetermined plan and the intention for most interactions were to assess a situation. See [Figure 2](#).
- The content of the query codes was captured by the use of sub codes ([Table 1](#)), which identified the set of wayside objects, such as signals, or physical characteristics affecting train state, such as grade, that were the subject of the query. The most common sub codes for queries were “milepost,” “signal,” “grade,” and “speed restriction” indicating that these environment attributes are the most important for the engineer to update in real-time.
- Engineers vary greatly in their preferred speed profiles, as evidenced by the variation in where engineers began slowing their train. As a result, the location and nature of braking also varied. Different engineers also used different combinations of dynamic and air train braking. The lack of consistency makes it difficult to identify distinct overall driving strategies from only five subjects. This also suggests that a shared control system should enable engineers to modify driving profiles to align with their preferences.

For the NAC experiments, the most common interactions were CKP at 28 percent and EXC at 55 percent of all interactions with a Level 2 label. The frequency of EXC is unsurprising, as most control actions by the novice would have been prompted by an EXC interaction from the expert. The CKP interaction indicates an assessment of the current situation for cues that would trigger a pre-defined action sequence. The key idea is that the current mental task is to maintain situational awareness. The dominance of the CKP interaction over planning-focused interactions indicates that the expert’s primary task en route was looking for situational cues that might trigger strategic or tactical planning.

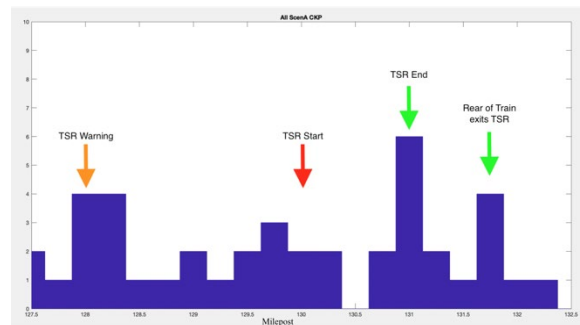


Figure 2. Frequency of the CKP interaction in novice-at-the-controls scenario, at temporary speed restriction.

CONCLUSIONS

The high frequency of the CKP interaction suggests that much of the freight engineer’s strategy rests on sets of triggers that determine the timing and type of actions that are made to accomplish the task goals. The situation is continually reassessed to determine if additional preconditions have been met and actions must be taken at that time. High-level decisions such as when to begin slowing the train are generally planned in advance, as are the set of preconditions that trigger an action plan. The driving strategy of a particular engineer will be determined by his or her own internalized goals, including, e.g., to stay below all applicable speed limits, but the frequency and consistency of the CKP interaction suggests that repeatedly checking cues to see if they satisfy



preconditioned schema is fundamental to train handling behavior (Endsley, 1995). The implication of the data from this study is that engineers largely act as situation assessors. In other words, train driving skill requires the execution of a pre-defined set of actions pursuant to a set of preconditions, and it is the engineer's job to identify these preconditions and determine if they have been met.

FUTURE ACTION

Previously in this project, researchers created a prototype of a shared speed control system that incorporated insights from this work. Specifically, the system conveyed information, facilitated re-planning (i.e., according to preconditions), and enabled driving preference adjustments consistent with the patterns observed in this study. It also introduced a new layer of information that summarized the goals in different segments of the automatically generated plan (e.g., "save fuel," "go fast"). Finally, a second study will need to be conducted in the CTIL to test how the improved transparency and flexibility affect trust in and usage of the automated system, as well as overall performance with experts and novices.

REFERENCES

- Endsley, M. R. (1995). Toward a Theory of Situation Awareness in Dynamic Systems. *Human Factors: The Journal of the Human Factors and Ergonomics Society*, 37(1), 32–64.
- Price, R. (2020). *Assessment of the Expert Locomotive Engineer's Mental Model*

through Expert-Novice Interactions.
Department of Aeronautics and
Astronautics. Cambridge, MA:
Massachusetts Institute of Technology.

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CONTACT

Michael E. Jones
Engineering Psychologist
Federal Railroad Administration
Office of Research, Development and
Technology
1200 New Jersey Avenue, SE
Washington, DC 20590
(202) 493-6106
Michael.E.Jones@dot.gov

H. Kirk Mathews
Principal Research Engineer
GE Research
One Research Circle
Niskayuna, NY 12309-1027
(518) 387-6646
mathews@ge.com

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