

2018

Human Performance Modelling for Adaptive Automation

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Recommended Citation

Leva, MC., Wilkins, M. & Coster, F. (2018). Human performance: modelling for adaptive automation. XXII World Congress of the International Measurement Confederation (IMEKO 2018). IOP Conf. Series: Journal of Physics: Conf. Series 1065 (2018) 182002, doi:10.1088/1742-6596/1065/18/182002

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Funder: Science Foundation Ireland

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Human Performance Modelling for Adaptive Automation *Journal of Physics: Conference Series*

To cite this article: MC. Leva *et al* 2018 *J. Phys.: Conf. Ser.* **1065** 182002

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Human Performance Modelling for Adaptive Automation

Journal of Physics: Conference Series

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Abstract. The relentless march of technology is increasingly opening new possibilities for the application of automation and new horizons for human machine interaction. However there is insufficient scientific evidence on human factors for modern socio-technical systems supporting the guidelines currently used to design Human Machine Interfaces (HMI) (ISA 2014). This dearth of knowledge presents a particular risk in safety critical industries. The continuing 60–90% of accidents currently that are rooted in Human Factors (HF) and the rapid developments in the Internet of Things (IoT) and its novel automation archetypes means that the requirements for new interfaces are becoming more demanding, and creating new failure modes. To address this gap it is necessary to face the issue of modelling the human factor element and be ready to incorporate that knowledge into the design of adaptive automation.

1. Introduction: automation and the paradox of automation

It's clear that automation has provided enormous gains to society. Safer and more efficient factories; faster emergency, and fire response; better decision support are only a few of the benefits.

In most process industry and manufacturing applications, automation has reached a point where the human operator supposedly just sits back and monitors the operation. In safety critical industries some of those automation choices are also dictated by process logic such as the need to execute a task that requires faster responses than humans possess. However as far back as 1983 Dr. Lisanne Bainbridge, a psychologist at University College London, was one of the first to rigorously study the ramifications of efficient and reliable systems and express the other side of the coin: the “Irony” of Automated systems: efficient automated systems reduce the need for human effort, but make human involvement even more critical. An operator that becomes detached from the actual processes in the plant because automation is doing practically everything will in fact have a very hard time understanding what is going on when that automation fails (the “Out-of-the-Loop syndrome”).

The paradox of automation has three strands to it.

1. First, automatic systems may foster a less in depth expertise from the human side by being easy to operate and by automatically correcting mistakes.
2. Second, even if operators are expert, automatic systems erode their skills by removing the need for practice.

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3. Third, automatic systems tend to fail either in unusual situations or in ways that produce unusual situations, requiring a particularly skillful response difficult to master even for expert users.

A more capable and reliable automatic system may make the situation worse.

This is something that touches us very closely, and we can remind ourselves of some examples where this interaction played a critical role with catastrophic consequences. For example the Airbus 330 automated system overrode by the human pilot on Air France Flight 447 on its journey from Rio to Paris in May 2009, causing it to crash. The IoT and the increased level of layers of complexity in efficient and pervasive automation will make the need to cater for the interface with the humans more important, not less. Nowadays the possibilities to choose what information to display and how to display it are nearly endless however do we really know how to design for best results for human machine interaction?

Are we ready for the upcoming challenges of designing for human machine collaborations?

2. Levels of Automation

When talking about the level of automation it is important to be able to distinguish between the different configurations it can offer with respect to the human computer interaction. One established taxonomy for this is defined by Endsley and Kaber (1999), which identifies 10 levels of automation implemented by four generic functions (i.e. monitoring role, generating role, selecting role, implementing role). However a simpler but perhaps more practical model might be taken from Wickens (2000). This model defines six levels of automation and three stages of automation as shown in Table 1.

Table 1. Wickens' Taxonomy for Levels of Automation (2000)

Stage 1: Information acquisition and analysis		Stage 2: Decision and choice	Stage 3: Execution
High (many features)*		High: automation will	High: Automation
	6	Choose	
	5	Choose unless human vetoes	
	4	Choose if human approves	
	3	Recommend one option	
	2	Recommend multiple options	
	1	Do nothing (human choice)	
Low (no features)			Low: Manual

3. Automation and workload balancing mechanisms

A fluctuating workload might be balanced by modifying the distribution in multiple ways.

- Distribution in time
- Distribution in executing entity
- Distribution in available processing power
- Distribution in priority

Distribution in time is basically a task scheduling activity. A priori knowledge of workload associated with certain tasks can be used to plan for a certain workload over time. This should be the basis of any workload balancing strategy, but does not account for unforeseen situations (like process upsets). Ad-hoc changes to the schedule might be difficult because many tasks and procedures, once started, do not allow for pausing and picking up at some point later in time. Distribution in executing entity means choosing who will do a specific task. This can be a choice between human or automation, but also a choice between different humans. Operators often work in teams, and an operator more experienced with the task might experience a lower workload than an inexperienced operator. Distribution in available processing power means splitting and dividing a task between multiple executing entities.

Typically this means getting more operators involved (e.g. during a plant start-up). Distribution in priority is a mechanism to help decide which tasks are most important at any given moment. This could mean tasks that would be seen as important during normal operation change to a lower priority during critical situations and postponed to a later time or even get dropped completely.

4. Intelligent Adaptive Automation

Scerbo (2007) discusses adaptive automation techniques that modify their level of automation based on models of operator behavior and workload, and more recently based on psychophysiological measures (Scerbo 2007). Hou, Banbury and Burns (2015) introduce the idea of Intelligent Adaptive Automation (IAA) that goes one step beyond Adaptive Automation as illustrated in Figure 1.

While flexible automation aims to reduce the negative effects of static automation by dynamically

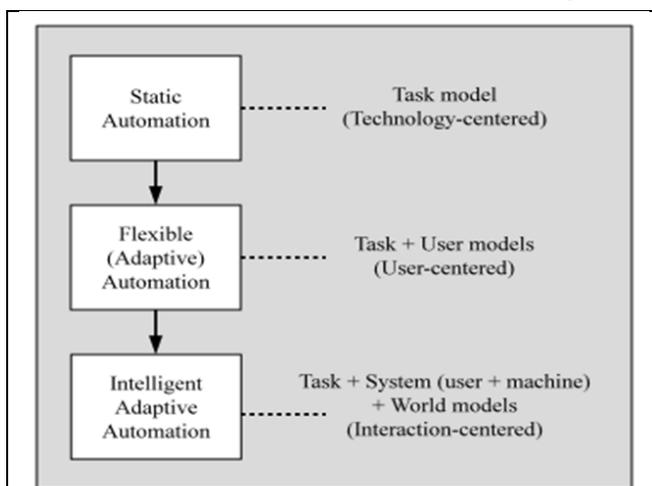


Figure 1. Automation technologies and design approaches.

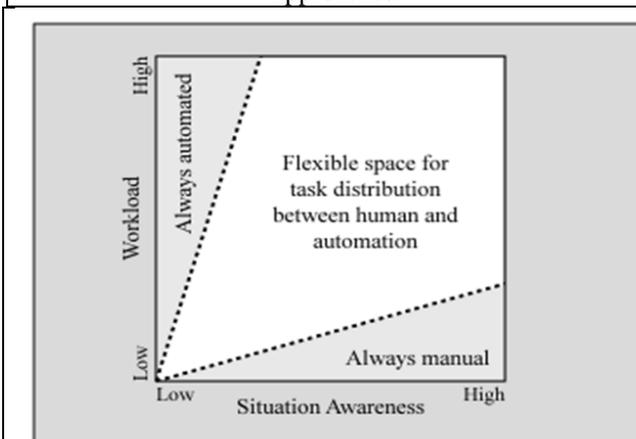


Figure 2. Trade-off between workload and situational awareness for automation decisions (Coster 2017).

shifting tasks between operator and automation, it is based on task and user models only and does not take external effects into account. Intelligent Adaptive Automation explicitly adds world models so the external effects are incorporated.

So Task, User and World models must be connected in a systematic way to accomplish Intelligent Adaptive Automation. The critical questions that need to be addressed are the ones proposed by Wickens (2000): a) what to adapt, b) how to infer? c) who decides?

It might be possible to determine what to adapt using the trade-off between workload and situation awareness as proposed by Coster (2017) (see Figure 2). For a specific task one can look at the workload imposed and the situation awareness provided by manually executing that task. Tasks that impose a high workload but provide little situation awareness should preferably always be automated, whereas tasks that impose little workload but provide high situation awareness should preferably always be done manually. The space of flexibility where (intelligent) adaptive automation can exist is somewhere between these extremes.

5. Final Goal: Reliable Human-Machine Systems

“The fundamental design issue is not to fight the individual causes of human

error but to create a work environment for actors that makes the boundaries to failure visible and reversible. In a competitive society faced with a very fast pace of technological change, this is very likely the only effective way to maintain operation of hazardous systems within the design envelope.”

(Rasmussen 1999). The manufacturing shop floor has changed dramatically since the early days of analogue dials and instruments but the publicly available data on human error rates (e.g. THERP, Swain and Guttman 1983) is still based on legacy technology. As computer based control systems continue to develop in scope and complexity and automation becomes ever more advanced, concrete data on human-system performance for modern HMI features are badly needed. Furthermore, Human Machine Interaction systems must nowadays consider real time adaptive automation functions to shape novel “human in the loop” design concepts. We can use machines to guide humans and the deductive power of humans towards better decisions. Mary Cummings Director of the Humans and Automation Laboratory at Massachusetts Institute of Technology is currently working on human-automated path planning optimization and decision support for pilots and she advocates that “Humans are doing a pretty good job, but they do it even better with the assistance of algorithms...when algorithms work with humans, the whole system performs better” (Cummings 2017). Hence, letting computers analyse masses of information generated during process upsets and using them to guide the operator about how to alleviate the incident will help to manage the operator mental workload in stressful situations (Wilkins 2017). The new technology will provide the long-term benefit of grounding the evaluation of human performance for operators in safety critical domains in a faster, cost-effective and more reliable manner. This sets up the conditions for disruptive innovation for better design in risk sensitive markets such as the large manufacturers considered for our test beds, providing much needed scientific evidence for the ISO Technical Committee 159/SC 4 and placing Human Factors at the core of technological development. One of the envisaged technological developments is moving towards HMI adaptive features for safety critical scenarios. Upcoming R&D efforts need to embrace the challenge and offer a model to move beyond a rigid design-operation sequence in favour of a circular approach based on adaptive automaton learning feature in the HMI.

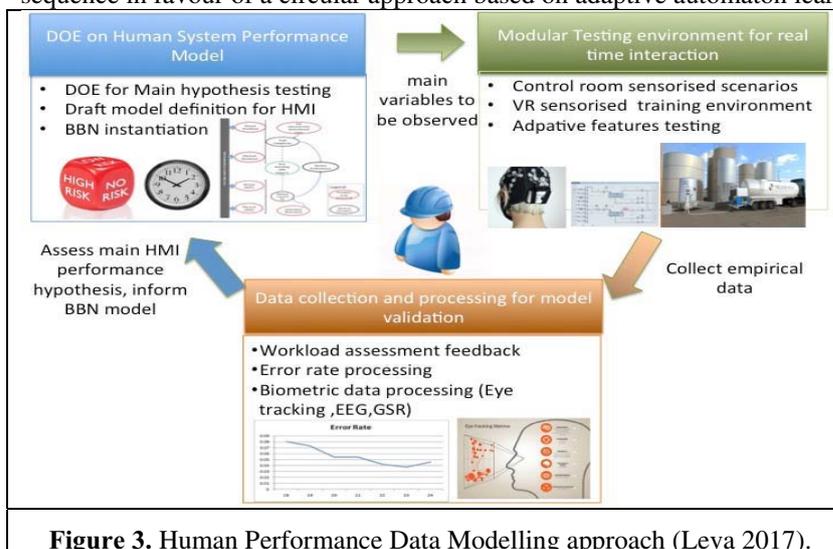


Figure 3. Human Performance Data Modelling approach (Leva 2017).

The research project envisaged by the authors will cover three keystones:

1. The first theme will provide the theoretical context for the research and produce the overall model to be tested and evaluated in the form of a Bayesian Network (BN), which can offer the advantage of providing a clear cause and effect model for human operations explicitly representing the assumptions. The model can then be verified and updated as new empirical evidence becomes available.
2. The second will develop a modular testing environment to harvest real time sensorial and scenario data providing a unique resource dedicated to investigating human performance in complex work environments. The environment can also be used to test adaptive features in HMI.
3. The final theme is dedicated to the processing and analysis of the empirical data collected from the experimental environment to test and validate the model. Figure 3 describes the interaction between these three elements.

In summary the key goals are: (1) To develop a world-leading human-machine interaction model able to account for dependencies in a safety critical system, acquire new data and “learn” from it using

BN; (2) To achieve as an interim scientific breakthrough the development of a sophisticated, sensorised environment capable of providing a multidimensional, dynamic assessment of human performance in high-risk context as well as new adaptive man-machine features. (3) To build a new, publicly accessible database fed by empirical data collected from the laboratory and calibrated against real world experience and historical data; (4) To demonstrate the application of the model in providing real-time early detection of human-system critical conditions triggering early intervention and decisions supports aimed at avoiding or mitigating accidents.

Acknowledgments

One of the authors would wish to acknowledge the funding received from Science Foundation Ireland as a contribution towards the work underpinning material for this paper.

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