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Toward an objective measure of automation for the electric grid

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Abstract

The impact of automation on human performance has been studied by human factors researchers for over 35 years. One unresolved facet of this research is measurement of the level of automation across and within engineered systems. Repeatable methods of observing, measuring and documenting the level of automation are critical to the creation and validation of generalized theories of automation's impact on the reliability and resilience of human-in-the-loop systems. Numerous qualitative scales for measuring automation have been proposed. However these methods require subjective assessments based on the researcher's knowledge and experience, or through expert knowledge elicitation involving highly experienced individuals from each work domain. More recently, quantitative scales have been proposed, but have yet to be widely adopted, likely due to the difficulty associated with obtaining a sufficient number of empirical measurements from each system component. Our research suggests the need for a quantitative method that enables rapid measurement of a system's level of automation, is applicable across domains, and can be used by human factors practitioners in field studies or by system engineers as part of their technical planning processes. In this paper we present our research methodology and early research results from studies of electricity grid distribution control rooms. The rapid transformation of the electric grid to a modern, two-way, computer-based automation system offers the human factors community a rich research environment because the impact of this rapid increase in automation on human operators is poorly understood. Using a system analysis approach based on quantitative measures of level of automation, we provide an illustrative analysis of select grid modernization efforts. This measure of the level of automation can be displayed as either a static, historical view of the system's automation dynamics (the dynamic interplay between human and automation required to maintain system performance) or it can be incorporated into real-time visualization systems already present in control rooms.

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1. Introduction

The impact of automation on human performance has been studied by human factors researchers for over 35 years. One unresolved facet of this research is measurement of the level of automation across and within engineered systems. Repeatable methods of observing, measuring and documenting the level of automation are critical to the creation and validation of generalized theories of automation's impact on the reliability and resilience of human-in-the-loop systems. Numerous qualitative scales have been proposed[1-4] and some of these have been applied to a few work domains. However these methods require subjective assessments based on the researcher's knowledge and experience, or through expert knowledge elicitation involving highly experienced individuals from each work domain.

More recently, a quantitative measure has been proposed[5], but is yet to be widely adopted, likely due to the difficulty associated with obtaining a sufficient number of empirical measurements from each system component. Our research goal is to create a quantitative method that enables rapid measurement of a system's level of automation, is applicable across domains, and can be used by human factors practitioners in field studies or by system engineers as part of their technical planning processes. Our approach begins from the perspective of human-machine interfaces, rather than task sequences or task networks which are fundamental to other methods[4-6], but can be time consuming to discover and document in sufficient detail. In this paper we present our research methodology and early results from studies of electricity grid distribution control rooms. The rapid transformation of the electric grid to a modern, two-way, computer-based automation system offers the human factors community a rich research environment. Advocates for transformation of this critical national infrastructure argue that a modernized electric grid will enhance situational awareness, increase consumer engagement and foster greater integration of renewable energy sources. A current focus of grid modernization efforts is on the incorporation of sophisticated protection units that are self-regulating and can eventually act in concert throughout a distribution grid to automatically isolate and ultimately restore service interruptions. This trend towards increasing levels of automation brings with it the threat of decreased situational awareness in control room operators and less effective human performance during system[6]. With this transformation, unprecedented amounts of data are now entering control rooms, data that must be translated into actionable events by system operators in real time. The grid is also becoming less predictable, with the influx of intermittent renewables, electric cars, demand response programs, and greater storm activity. Yet how these changes impact control room situational awareness and decision-making and the resulting impact on grid resilience is poorly known. Using a system analysis approach based on quantitative measures of level of automation, we provide an illustrative analysis of select grid modernization efforts. Human performance trade-offs are discussed and guidelines for further research activities are proposed.

2. Method

Objective and quantitative methods of measuring a system's level of automation are needed to advance the development and evaluation of more generalized theories of automation and to better understand automation's impact on the reliability and resilience of human-in-the-loop systems. A useful quantitative method should be succinct, allowing for rapid measurement of a system's level of automation, and also detailed enough to describe the multiple roles of automation that support system function. While an electricity grid distribution system is used as a case study in this research, we describe a generalized method that is applicable across work domains.

Our approach to quantifying automation applies a generalized definition of automation: automatically controlled operation of an apparatus, process, or system by mechanical or electronic devices that take the place of human labor[7]. We have modified this definition for the electric grid, which has a mix of automated and mechanical elements, such as breakers and fuses, to ensure the safe delivery of electrical energy. Our definition of automation, as it applies to the electric grid, is the following: automatically controlled operation of the distribution grid by mechanical or electric devices that optimize the flow of electrical energy and information for a fully controllable, interconnected and flexible distribution system.

Automation systems are typically designed to fulfill generalized functions supporting overall system functionality. Prior work on characterizing automation has produced similar organizational structures that describe the purpose of a particular automation subsystem or set of tasks that support the overall system functionality.

Endsley and Kaber[2] describe four generic functions intrinsic to numerous modern work domains. They labeled these four functions “monitoring”, “generating”, “selecting” and “implementing.” Parasuraman, Sheridan and Wickens[4], used a four stage model of human information processing to define four classes of automation functions which they labeled “information acquisition”, “information analysis”, “decision and action selection”, and “action implementation.” For a concise history of level of automation taxonomies, see the introduction of Rottger, Bali and Manzey[8]. We use the stages described by Parasuraman, et. al. because they are consistent with human and computer information processing models. In the section 2.1, we discuss methods to quantify the level of automation within each stage. In section 2.2, we describe a new measure of automation and in section 3 we describe the application of our method to an electricity distribution grid system.

2.1. Quantifying level of automation

Previously proposed methods for quantifying automation typically examine the proportion of tasks allocated to automation compared to the total number of tasks, both automated and human-executed, required to meet system performance goals. We first examine one such method in detail and then describe an alternate approach that does not require a complete task analysis by applying the definition of automation at its lowest level – allocation of actions between humans and machines. Wei, Macwan and Wieringa[5] calculate the “degree of automation” of a system by assigning weights to each task based on the task’s impact in each of three categories: task effect on system performance, task demand load, and task mental load. Task demand load is primarily measured as the physical demands placed on humans interacting with a given system and task mental load is primarily measured as perceived workload. The sum of the manual task weights within a category is then ratioed to the sum of all task weights in that category. This ratio is subtracted from unity to produce a metric that quantifies the fraction of automation dedicated to each category (see equation 1, where t_i is a binary value set to one when the task is accomplished by automation, or set to zero when the task is accomplished by humans and w_i is the task weighting).

$$DofA = 1 - \frac{\sum_{i=1}^{N} t_i w_i}{\sum_{i=1}^{N} w_i} \tag{1}$$

In practice, it is difficult or time consuming to empirically determine appropriate weights for each task-category combination. In a survey of work citing Wei’s method, we were unable to find any that report calculated values for degree of automation for fielded systems and only a few reported values for simulation-based systems[9-15]. In the next section, we describe a quantification method to support generalized theories of automation by applying the definition of automation at its lowest level – allocation of actions between humans and machines.

2.2. Real-time measurement of level of automation

Our study builds on Parasuraman and Wei’s foundational work but brings near real-time data from the computerized supervisory control and data acquisition (SCADA) systems widely used in electric-grid and other industrial operations that are essential to the reliable and efficient control of critical infrastructures. The rich information stores created by SCADA systems provide the essential information needed to measure a system’s level of automation using simple text processing and time series analytics. Information identifying the nature and frequency of actions executed by humans and machines is available in near real-time. These information stores are also rich in metadata relating actions to specific subsystems and overall system performance.

For example, over the last decade smart grid technologies have been incorporated into electricity distribution systems to increase the number of points on the grid that are monitored for important system parameters such as voltage and current. New fault protection devices, for example reclosers can operate in a fully automated manner to isolate faults and restore service interruptions due to transient fault conditions. Even when they are not operating in a fully automated manner, these devices can be operated remotely by control room operators to achieve the same fault isolation and service restoration functions. Many, if not all, of the monitored parameters and executed actions, both by humans and machines, are recorded and stored in archival databases.

Our quantification method begins with an inventory of system functions. In the case of electricity distribution systems, some example system functions are the delivery of electrical power, the location and isolation of faults, or sources of power interruptions, and service restoration. Next, an inventory of operator-to-system interfaces is completed to rapidly identify the interfaces and system components that support each system function. These elements are then categorized as either “information processing” or “control point” based on their primary usage. By interviewing system operators and engineers, we were able to identify and create a matrix of keywords in the SCADA logs that indicate actions executed by humans or machines for each system element and stage of automation. Table 1 provides an example keyword matrix based on SCADA data from our utility partner.

Table 1. Example SCADA log keyword matrix. Table entries where the SCADA logs did not include sufficient information to calculate the level of automation are maked as not applicable (N/A).

	Information Acquisition	Information Analysis	Decision Selection	Action Implementation
Machine				
Automated Action	RTU no on/off line	low limit exceeded	N/A	device change of state [OPEN, OFF]
Result of operator commanded action	N/A	N/A	N/A	control succeeded [OPEN, CLOSED, TAG]
Operator	N/A	N/A	N/A	
Command machine action	N/A	operator control, note added	N/A	Operator control [OPEN, CLOSED, TAG]

The matrix of keywords can then be used to process SCADA log files, either retrospectively or in real-time, to create two separate time series for each stage of automation. For example, see Fig. 1. One time series contains markers for all actions executed by humans or machines; the other contains markers for actions executed only by machines. Processing these time series for each stage of automation with a moving window averaging filter produces two new time series that represent the average number of actions within each window as shown in Fig. 2. Finally, the level of automation time series is calculated as the point-to-point ratio of the window-averaged number of actions executed by machines to the window-averaged number of all actions executed within each stage of automation. This measure of the level of automation can then be displayed as either a static, historical view of the system’s automation dynamics (the dynamic interplay between human and automation required to maintain system performance) or it can be incorporated into real-time visualization systems already present in control rooms.

A more succinct representation of the level of automation is achieved by arranging the values in a matrix of system function by stage of automation. This matrix can be treated as a set of four-dimensional vectors, where each dimension represents one of the stages of automation. The overall level of automation for each system function can be calculated by constructing a total vector for each function using vector addition. The direction cosines of the resulting vector describe the allocation of automation across each of the four stages of automation for each system function. The direction cosines of the vector sum over all functions describe the allocation of automation for the overall system. This multidimensional approach maintains the generality and rich interpretability of the stages of automation model and provides objective, quantitative measurements for comparing systems within and across work domains.

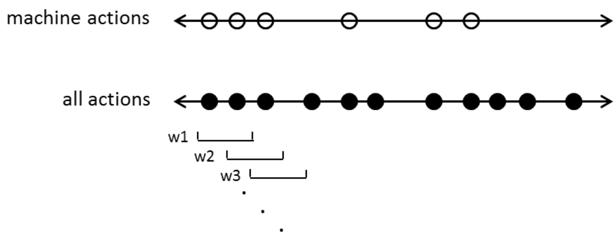

Figure 1. Example time series for a given stage of automation. Actions executed by machines are shown on the upper time line. All actions are shown on the lower time line. Windows used for averaging are indicated by w1, w2, etc. By comparing the two graphs, one can readily observe the dynamic relation between machine actions (automation) and all actions, the latter including operator actions.

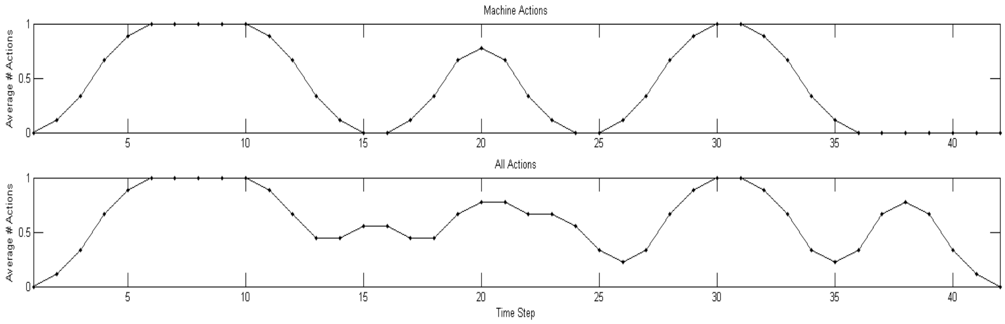

Figure 2. Example results of moving window averaging. The time series for level of automation is calcuated as the point-to-point ratio of machine actions (upper time line) to all actions (lower time line).

When the level of automation approaches zero, system operations require more effort from system operators who are also likely to experience higher workloads. If low levels of automation are regularly associated with certain subsystems or devices, investment in additional automation solutions or changes in workforce allocation may be warranted to reduce operator workload or improve efficiency. Conversely, when the level of automation is routinely high, the system functions with little operator intervention. During these times, system operators may be vulnerable to distraction or complacency, both of which can result in decreased situation awareness. As identified by Onnasch et. al.[6] it is at these times that system performance is most vulnerable to automation failures.

3. Application to electricity distribution utility operation

SCADA log data from 31 days of grid operations were provided by a distribution utility located in the Northeast United States. Table 1 shows an example of the SCADA keyword matrix used to calculate the level of automation time series. It is important to note at this point that in some cases, the information necessary to make this measurement may not be recorded or accessible. For this case study, it is not possible to calculate the degree of automation at the information acquisition stage or the decision selection stage. Future versions of SCADA logging systems could be augmented to provide additional information describing actions at each stage of automation. To illustrate application of this method, the level of automation was calculated over all stages of automation and system functions. However it should be noted that as more information is made available in SCADA logs, it is possible to calculate the level of automation for each stage of automation. It was also determined that the SCADA logs did not contain sufficient information about each action to accurately assign a duration specific to each action. Therefore, for this example, we assigned a duration of five minutes to each action. The width of the averaging window was set to ten minutes. The moving window averaging was performed in MATLAB using the filtfilt function included in Signal Processing Toolbox[16] to remove lag effects of filter charging. In real-time applications, only retrospective information is available and filter lag effects must be accounted for when displaying the level of automation as a function of time. Fig. 3 shows the calculated level of automation over 31 days. On the ninth day of this time period, a strong snow storm entered the region causing widespread damage and power interruptions. This event, and efforts by control room operators and field crews to restore power, is apparent in the level of automation. After a stable period of highly automated operation from day 4 to day 9, the level of automation oscillates frequently between low and high automation beginning at day 9 as automated systems perform fault isolation functions and human operators respond to alarms and work to restore service.

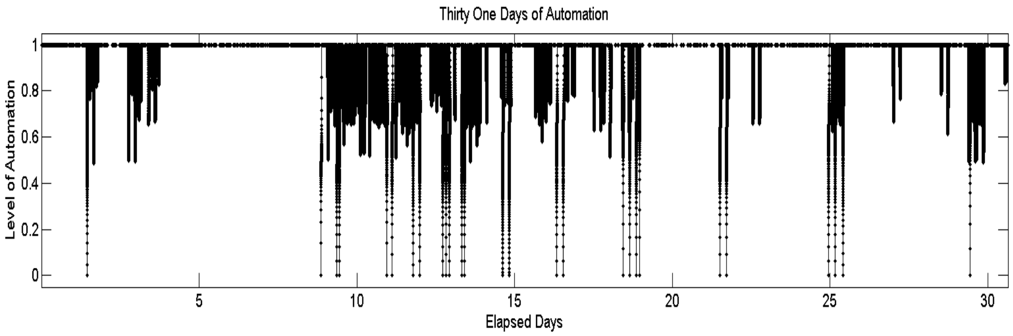

Figure 3. Levels of automation vary during 31 days of operation. Note the low levels of automation beginning at day nine when a strong snow storm began.

A more detailed example of a single power interruption event is shown in Fig. 4 and Fig. 5. Fig. 4 shows a schematic of a substation and upstream recloser affected by a device failure. Fig. 5 shows the level of automation from the time of the first device failure at approximately 23.5 hours to the time of service restoration at approximately 25.75 hours. The event began with a device failure in recloser R2, which caused the upstream breaker, R1, to open automatically. As shown in Fig. 5, the immediate system response to the initial device failure was fully automated. Later, at approximately 24.75 hours and 25.5 hours, operators performed two separate remote switching operations as part of their service restoration efforts. As illustrated in Fig. 5, these switching operations began as fully manual processes and transitioned to fully automated processes as computerized information analysis actions, such as threshold alarms, were triggered due to the new operating configuration of the electric grid.

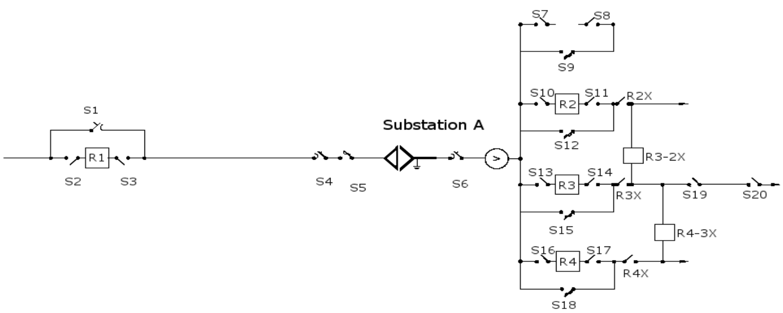

Figure 4. A schematic representation of the grid section affected by the failure of device R2. Angled lines represent switches and are identified by the letter S and a unique number. Squares represent recloser devices and are indentified by the leter R and a unique number. Switching operations, opening and closuing switches as needed to sectionalize and reroute power on the grid, constitute a large part of an operator’s job.

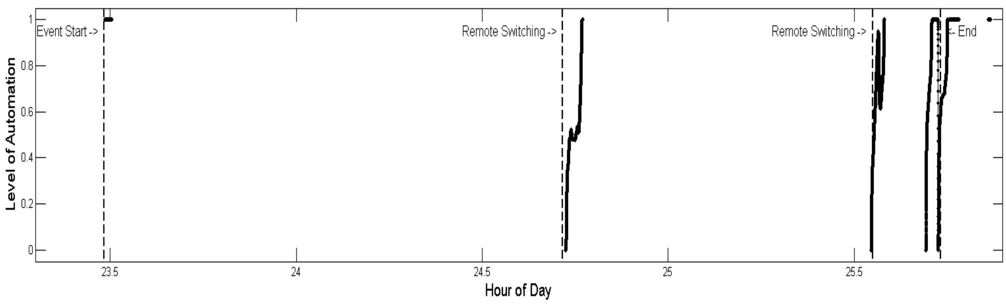

Figure 5. Level of automation from device failure to completed service restoration. Note the transitions from low to high automation as switching activities are conducted around 23.75 hours and 25.5 hours.

4. Summary and conclusion

The method described in this paper makes it possible to measure and track the changing level of automation as a critical infrastructure system moves through its natural system dynamics. It is sufficiently general to be applied across different work domains and critical infrastructure systems. Because the method does not require a complete task analysis of the work to be studied and does not require assignment of task weighting factors, it can be applied more quickly than other quantification methods. It provides a new, richly detailed view of important factors that may affect overall system performance, including operator workload and weaknesses or gaps in system automation. These moment by moment details can be analyzed over simple periodic time periods (for example, weekly, or monthly), during critical events (such as storms or system upgrades), or for specific subsystems. As noted in sections 2 and 3, all of the information and actions necessary to measure the level of automation at each stage may not be logged by current systems. For example, the SCADA systems we work with do not include specific information related to the decision selection stage. We believe this is an opportunity for human factors researchers and engineers to collaborate with vendors who support critical infrastructure systems so that the necessary information can be made available. These analyses described here can be used to guide infrastructure investment decisions concerning personnel allocations and infrastructure investment decisions by highlighting subsystems or operating conditions where increased automation is needed. These analyses can also guide human-computer interaction design for future control rooms. For example, when automation is high, there is an increased risk of human complacency. Future systems could be designed to maintain operator engagement during highly automated time periods so that situational awareness is maintained. The increased understanding of the system dynamics pertaining to level of automation provided by this method, and the discussed analyses, can be used to improve the performance and resiliency of critical infrastructure systems.

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