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In the push to develop smart energy systems, there is increasing focus on how to design systems that measure and predict user behavior in order to effect optimal energy consumption. While such focus is clearly an important component in the success of these future systems, substantially less attention is paid to the human on the other side of the energy system loop – the supervisors of power generation processes, the proverbial men (or women) behind the curtain. Out of sight and sadly in terms of technological advancements, out of mind, today these operators perform high risk jobs in often data-rich, but information-impoverished settings. For these operators, pervasive computing of the future will likely add to an already complex array of data streams, and introduce a new layer of supervisory complexity in response to the goal of dynamically adapting energy management.

The Three Mile Island nuclear power plant accident in 1979 was caused primarily by operator misunderstanding of sensor data from an overwhelmingly complex control panel [1]. More recently in 2003 in the Northeast, operators were not able to both see and understand critical system states for nearby power grids, ultimately leading to the largest blackout in North American history which contributed to at least 11 deaths and cost an estimated $6 billion [2]. In these high profile cases, and in countless other more minor electric and nuclear power plant incidents, a significant problem was and continues to be the lack of explicit design to support rapid data aggregation and information visualization to support supervisors' time-pressured decision making.

The development of smart energy systems that leverage pervasive computing could further add to the workload of these supervisory control operators who will have to predict possible power plant load and production changes due to environmental and plant events, as well as dynamic system adaptation in response to customer behaviors. Contrary to many assumptions, the insertion of more automation, both in terms of distributed sensors and algorithms to post-process data for operators, will not necessary reduce workload, nor necessarily improve system performance. These concepts are explored in more detail in the following sections.

Supervisory Control and Workload in Power Generation

Current power generation operations are highly automated. In normal, day-to-day operations, automation controls the adjustment of system parameters, while human operators generally take the role of system supervisors, monitoring system states and typically intervening in only non-monitoring operations, such as responding to an alarm, managing a plant start-up, or overseeing other off-nominal operations. However, in present-day power generation operations, while the system itself is highly automated, little automation is used to support and augment supervisor decision-making and performance, especially in time-critical, system anomaly situations. Indeed, while digital displays are replacing analog ones in current control rooms, many plant displays, particularly in the nuclear reactor realm, simply graphically replicate analog displays, effectively keeping the look and feel of 1960s-era control rooms.

Central to a system control paradigm with such high levels of automation is the idea of Human Supervisory Control (HSC). HSC assumes that a human operator will monitor a given system, taking on the role of system supervisor or manager [3]. This role suggests that the operator is not tasked with operating low-level system actions, though the operator can intervene if and when the situation requires. This relationship between the system and an operator is commonly termed “human on-the-loop”, rather than “in-the-loop”, directing focus away from constant, direct control toward the supervisory control paradigm.

Figure 1 depicts a conceptual model of HSC in terms of two human operators controlling two plants. This model indicates that the control of the physical system (labeled “Plant”) is the responsibility of the automation (labeled “Automation”). The human operators (“Human 1” and “Human 2”) supervise and interact with the system (“Plant”) only through the automation. In addition to plant supervision responsibilities, human operators will be required to monitor and synthesize different types of information coming from the smart grid system to ensure safe and efficient plant operation. Though this additional information may aid operators in decision making for plant operations, the increase of information could increase operator workload.

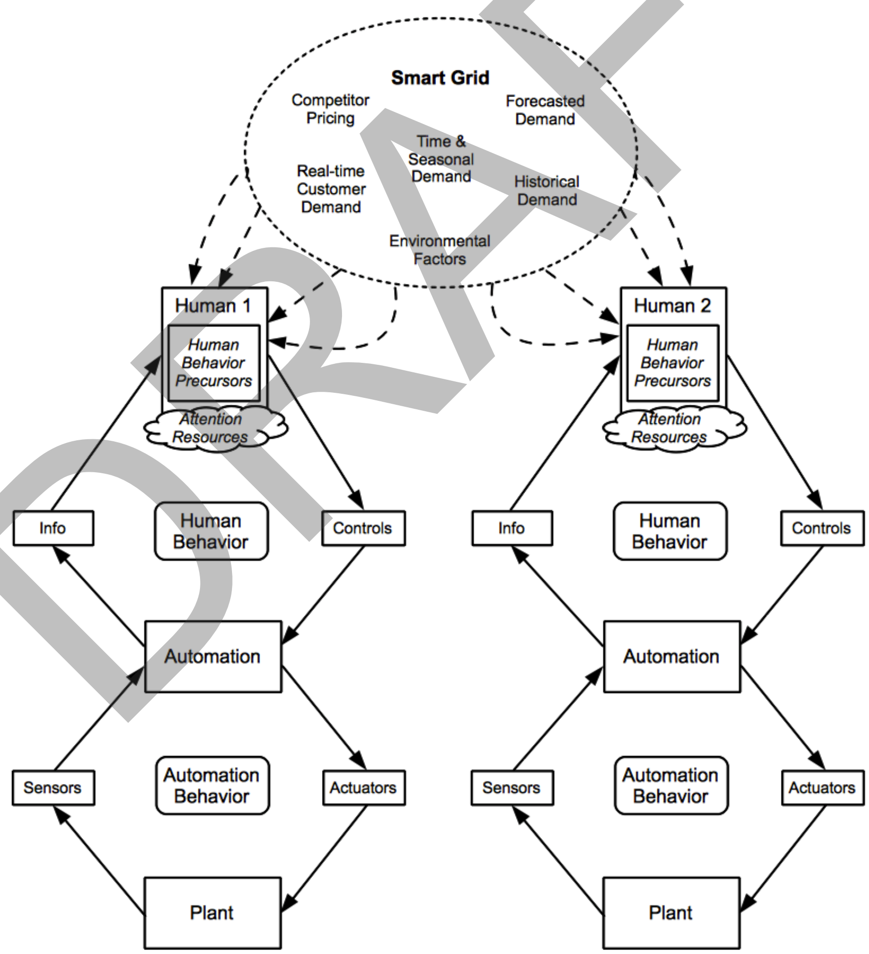

Figure 1: HSC model for power generation systems (modified from [4]).

Given that the introduction of pervasive computing in smart grid settings could increase the workload for supervisory control operators, especially those without any advanced decision support, a seemingly reasonable solution is to introduce more automation in terms of grid management. Automation is commonly introduced into HSC systems to reduce the likelihood of operator error by reducing operator workload. This relationship is not universally true, however as increased automation often just changes the nature of the work [5-7].

Several studies reviewed by Parasuraman, et al. [8] suggest that automation in aircraft cockpits has been known to actually increase workload, rather than decrease workload as intended. Interestingly, there is little evidence supporting the idea that operators will delegate tasks to automation when workload is high [9, 10]. It is unclear whether these relationships can be generalized to the power generation domain, though several similarities exist between automated aircraft control and power generation systems. For example, monitoring an aircraft on autopilot contains similar monitoring tasks as monitoring a power generation system. Alarms or warnings activate when the system reaches a state outside of predefined parameters and operators are then expected to take over some level of control of the system.

As evidenced by the TMI accident and the 2003 Northeast blackout, both of which required operators to move from a monitoring state to an emergency action mode with significant time pressure, operator lack of understanding of what the automation was doing, often called mode confusion, exacerbated the problem. Mode confusion occurs when an HSC operator attempts to take control of a highly automated system, but does not understand the current mode of automation (i.e., the goals or objectives the automation is attempting to achieve). In both aviation and power generation systems, this lack of automation understanding can and has caused catastrophic human-system failure due to confusion over who is in control (the human or system), especially when the desired goal state of the operator differs from that of the automation.

In the development of smart energy systems, it remains an open question how supervisors of power plants will respond to the inevitable addition of higher layers of automation. Human supervisory control operators of power generation processes will need to understand how a smart energy management system could affect the power generation process, both in terms of safety and efficiency. However, significant automation will be needed to both manage these processes as well as data representation so the operator understands what the automation is doing. Such nested layers of automation increase system opacity, and a lack of automation transparency, i.e., a lack of sufficient and intelligible feedback, is causal factor mode confusion [6, 8].

Designers of future smart energy systems will need to consider the unintended consequences of possible mode confusion and increased workload for HSC operators caused by increasing levels and layers of automation, particularly for emergency scenarios. This will require more advanced display technology in the form of integrated software decision support tools that leverage more advanced information visualization and data fusion techniques for both current and predicted state representations. Furthermore, the design and operation of future smart energy systems will require socio-technical changes, i.e., organizational and regulatory policies and procedures will also have to be updated or changed outright. For example, it remains unclear how smart grid technologies meant to improve efficiency, but ultimately linked to power generation safety, will influence operating procedures and certifications.

The Need for Human Oversight of Automated Planning

The assumption that increased automation can reduce workload for operators in futuristic smart energy systems is not only naïve in terms of workload management as previously discussed, but this also ignores the critical role that the human operator plays in supervisory control systems in that they can apply reasoning in situations where automation cannot be absolutely correct in all situations.

One of the most critical aspects of any integrated sociotechnical system design with significant embedded autonomy is that of role allocation i.e., who (automation and/or human) should perform which functions and when? According to early research examining human-computer allocation in the air traffic control domain, humans and computers (called machines at that time) possess the respective strengths listed in Table 1, known as Fitts' List [11]. This early attempt at role allocation between humans and computers recognized that automation can be used to support, not necessarily replace, human operators in large scale computational decision-making tasks.

As depicted in Table 1, algorithms can execute repeatable, precise, and speedy computations, which are ideal for complex optimization problems such as those inherent in pervasive computing and smart grid environments. However, automation can be inflexible and unable to adapt to changing situations. Though fast and able to handle complex computation far better than humans, computer optimization algorithms are notoriously "brittle" in that they can only take into account those quantifiable variables identified during the design stages as critical [12, 13].

Table 1: Fitts' List for Human-Computer Role Allocation (adapted from [11]).

Humans are better at:	Computers are better at:
Perceiving patterns	Responding quickly to control tasks
Improvising and using flexible procedures	Repetitive and routine tasks
Recalling relevant facts at the appropriate time	Reasoning deductively
Reasoning inductively	Handling simultaneous complex tasks
Exercising judgment	Fast and accurate computation

In contrast to automation brittleness, humans' strengths in planning environments are their abilities to improvise, learn, and reason inductively, which are precisely the skills required to adapt to unexpected circumstances. This type of problem solving is called knowledge-based reasoning [14], during which humans make decisions under novel and uncertain situations, which are attributes inherent to supervisory control scenarios. In terms of managing the large data streams that will be generated in smart grid environments, automation will be critical in handling the bulk of problem solving and system management. However, just as evidenced by the 2003 Northeast blackout, even highly automated systems can be presented with a set of dynamic and unexpected variables states never envisioned in advance by designers, which can ultimately lead to catastrophe. So while smart grids of the future, with embedded complex algorithms to balance power input and output across a network, will be highly automated, they will not be able to be *completely* automated, primarily due to the inherent uncertainty in both the environment and the algorithms themselves.

While keeping the human in the loop for potential interventions for low probability events like a blackout is well established in the supervisory control literature, significantly less is known about if and how human operators can provide value in assisting embedded algorithms optimize system performance, which is the crux of smart grid operations. For future smart energy systems, every customer represents a node that may not always behave in an expected manner, which may cause problems between expectations and forecasts that do not match actual operating conditions. Given the complexity of such a large problem space with layers of uncertainty, it is not clear that algorithms will always be able to truly optimize in all conditions across what is effectively a decentralized network. While little research has examined how operators in decentralized energy networks can aid algorithms in optimizing system performance, recent research in supervisory control of unmanned vehicles sheds light on the capabilities of humans working collaboratively with algorithms to achieve superior performance in system optimization.

In the near future, the military envisions networks of decentralized unmanned vehicles (including air, ground, sea surface, and subsurface) that work together, with a human on the loop, to conduct resource allocation missions, e.g., using an array of unmanned vehicles to search remote, possibly hostile areas for enemies or victims. In these futuristic networks, each unmanned vehicle computes its best plan with some type of local negotiation with other unmanned vehicles, with no globally optimal plan since each vehicle strives to maintain the best plan with possibly limited information. The decentralized approach is superior to the centralized one in terms of protection against network vulnerabilities caused by bandwidth limitations and reliance on specific vehicles for critical tasks.

These decentralized network attributes have direct mappings in future smart grid energy environments, where smaller, decentralized spheres of localized smart grid control could be created, possibly managed by home and building owners. Just as in the network of decentralized unmanned vehicles, these smaller spheres could allow for local optimization of resources, without requiring more complex and resource intensive globally optimal network solutions at substations or utility-managed command centers. However, such nodes of local control still require some supervisory oversight, particularly in anomalous situations such as major power outages and extreme weather conditions.

Given that relatively high levels of automation are absolutely essential for the operation of these decentralized networks, but yet humans are needed at some level for system oversight, it remains an open question just how much human collaboration should be allowed and what the impact of human interaction could be for such a system. To partially address these issues, an experiment was conducted that examined how well a decentralized network of vehicles would perform if no human oversight was provided, as compared to how well the system would perform if a human operator was allowed to "tweak" the resource allocation and scheduling plans of the automation.

In this experimental setting, a network of five unmanned vehicles was given the task of searching as much of a predetermined area as possible, and then track found targets using a mixed integer linear programming algorithm. In the automation-only condition, the automation generated all plans, which were automatically approved and a human operator never changed the tasking or rate at which plans were generated. In the second condition, humans + automation, humans were allowed to update the algorithm's tasking or replan more often if they thought the automation was not performing adequately. The details of this experiment are provided in [15].

Figure 2 demonstrates just how much value added the human provided in terms of the two primary dependent measures, percentage of area covered and number of targets found. Three different workload levels were investigated to determine how both the automated planners and the operators would respond under changing workload conditions, i.e., the 30s/45s/120s factor levels represent the time between replanning intervals so that 30s represents high workload and 120s represents relatively low workload.

As can be seen in Figure 2, allowing a human operator the ability to evaluate and occasionally change an automated solution allowed the system to perform substantially better than if the automation was left alone. Of the six conditions shown in Figure 2, only for the 120s interval for the area searched metric was the automation-only approach statistically no different than the human-assisted mode, suggesting that the longer intervals between replanning were beneficial for the automation. However, for the targets found metric, the collaboration between the human and the automation resulted in more than 20% increase across all factor levels.

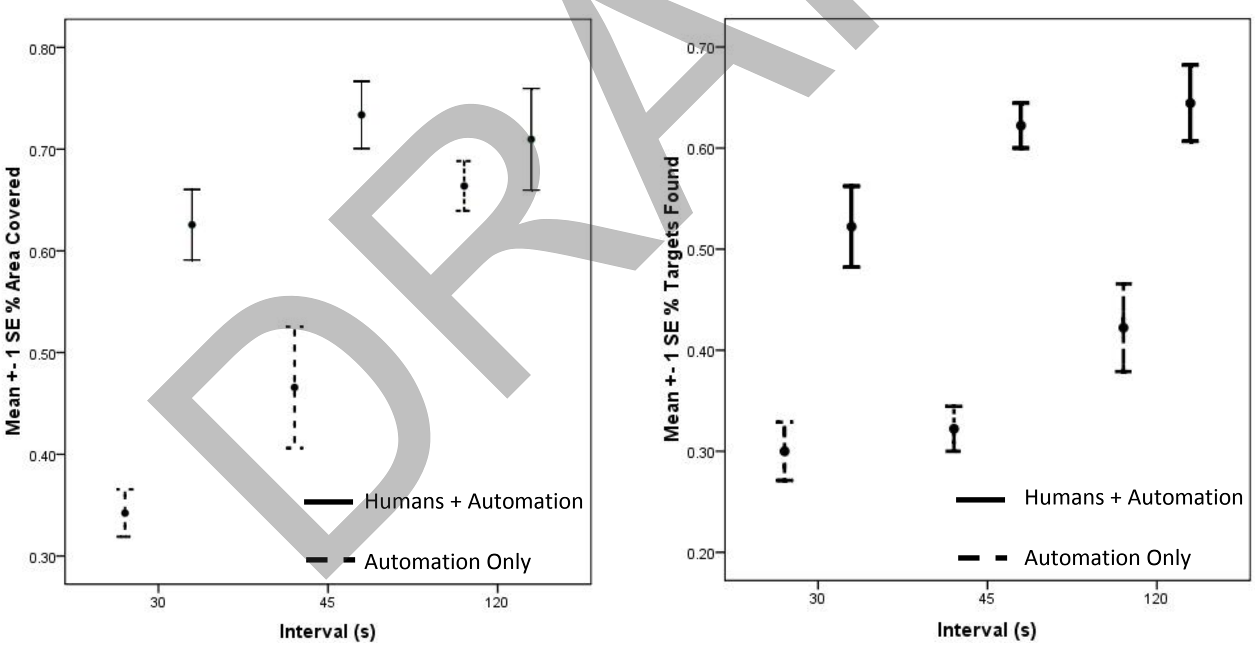

Figure 2: Value added by allowing humans to work with a planning and scheduling algorithm.

While the results in Figure 2 are for a decentralized unmanned vehicle planning and scheduling problem, they highlight the importance of understanding the benefit of human interaction in domains where automation is used for decentralized scheduling and resource allocation, which is likely in the future of smart grids. The human operator was critical in this domain because of the uncertainty inherent in the system. The autonomous planners on the unmanned vehicles operated with *a priori* cost functions coded by the algorithm designers, which theoretically generated an optimal solution, but in reality could be improved upon by *occasional* human judgment.

This temporal component of human interaction is important to consider because previous related research has shown that if operators intervene too much in such distributed planning systems, the overall system performance could suffer [16]. The key is determining some robust range of helpful human interaction. In addition, while military command and control settings possibly contain more uncertainty than power generation settings, there are many sources of uncertainty in smart grid system management that could lead to similar problems such as weather, customer behaviors, algorithm design, and system failures.

Conclusion

In the envisioned future of smart energy systems, pervasive computing systems will measure user behavior in order to infer behavior as a step to mitigate and optimize energy usage. Such systems will require significant embedded algorithms, as well as some level of human supervisory control, the proverbial man behind the curtain. We have shown here that in domains where uncertainty exists in the world as well as in probabilistic algorithms, which is clearly the case in behavioral inference, it is critical to consider the human role not just as a monitor of anomalous system states, but also as one of collaborator.

While it is generally recognized that in power generation environments, automation in the form of intelligent agents is needed in safety-critical monitoring tasks like fault detection, situation assessment or diagnosis, and response planning [17], unfortunately there is no organized effort that we are aware of to focus on developing algorithms and associated decision tools in support of supervisors that will manage futuristic dynamic and adaptive smart grids. Such research is needed to determine the required degree of interactivity between supervisory control operators and the automation central to a pervasive computing system, how to manage the voluminous data streams that will be generated by smart energy systems, and how to balance the competing objectives of safety and optimal energy production.

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