Measuring process control automation benefits through a human-machine function allocation analysis

Running Title: Measuring automation benefits

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Abstract

Often technology is introduced into manufacturing and process control environments to partially automate tasks too complex to fully automate. However, it is not always clear how to measure the benefits of such projects. More often than not, automation eliminates but also shifts human work, and broad productivity measures can fail to capture such changes. To this end, this effort describes a manufacturing case study that looks at human-machine allocation metrics involving a laboratory fermentation unit upgrade. Using a workflow monitoring and function allocation analytic approach, it was determined that upgrading an older microbial culture bioreactor (fermentor) to a new design with intelligent monitoring capabilities resulted in an approximate 17% reduction in dedicated human supervision. This workload reduction allowed scientists to spend less time on repetitive tasks and more time concentrating on other, more open-ended problems that require more expertise. However, the new technology increased human efforts across other functions, suggesting potential mitigation paths for future technology development. This effort illustrates that the impact of new technology on humans-machine tasking can be quantified through a function allocation analysis and also provide diagnostic information, both of which are critical in understanding any overall added benefit of intelligent systems.

Introduction

Increasing automation throughout process control plants and laboratories is seen as a way to reduce variability, lower costs, and increase efficiency. However, not all processes can be easily automated, and, in many instances, partial automation must be used where humans are needed to supervise one or more process elements. As technology matures, some elements of a process may be a candidate for automation, but it is often not obvious whether applications of partial automation have a clear benefit, especially when supervised by an operator is still required. In the context of this effort, ROI means that automation reduces human workload by effectively taking over human tasking, including human supervision. Such partial automation is not meant to replace human scientists but rather to free them from mundane tasking so they can work on more open-ended problems that require expertise. To this end, this article presents a case study examining how and to what extent the introduction of a new research fermentation unit with increased automation improved workflow processes through a function allocation analysis.

A critical aspect of the development of any advanced automated system is that of role/ function 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 (Fitts 1951). This and other similar efforts demonstrate that automation is generally good at repetitive tasks that require rapid computation, and humans are better at adapting to changing situations (Price 1985, Sheridan 2000, Cummings 2014).

Table 1: Fitts' List for Human-Computer Role Allocation (adapted from (Fitts 1951))

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

In process control plants and manufacturing settings, reliability, speed and adaptability are often the primary concerns in achieving optimal output. In these settings, function allocation between humans and machines/computers is often determined by the ease and cost of developing automated systems, with those functions deemed too costly to automate typically left for humans to manage (Guerlain, Jamieson et al. 2002). This decision then leaves operators in a supervisory role, who must then monitor the partially automated systems for problems or abnormalities. In addition, regulatory requirements could dictate the need for certain levels of human involvement, like those in nuclear reactors.

A Process Control Human-Automation Function Allocation Case Study

Pfizer, Inc. has a number of research and development (R&D) fermentation units for microbial culture expansion that are critical for early stages of vaccine development, and as new products become available, they look to upgrade such units. As is typical in process control domains, technology upgrades with improved functionality are generally seen as good for business. However, due to complexities in fully automating a process, "off-the-shelf" automation upgrades often introduce partial automation enhancements that do not address the critical needs of scientists and thus minimize the ROI of such an investment. In addition, it has been well-established across many domains that the introduction of automation often results in a potential shift or even increase in workload as humans are moved to supervisors of automation (Bainbridge 1987, Strauch 2018, Banks and Stanton 2019).

In order to determine how a newly-installed R&D fermentation unit affected scientist tasking and the balance of work between humans and a partially-automated system, a function allocation analysis was conducted that compared the workflow for the supervision of a cluster of older fermentors to that of upgraded fermentors with new automated features that contain the same microbial culture. The goal was to determine how the new fermentors impacted scientist workflows and how functional allocation and/or technologies might need to be redesigned to optimize efficiency and safety.

Method

In order to conduct a comprehensive function allocation analysis of an existing system like fermentation units that require human and automation interaction, the workflow processes associated with the systems under investigation must be observed. This requires observing scientists as they go about their tasks, with occasional clarifying questions about what and why scientists take particular actions. Such actions are core to any task analysis in general, but especially important in cognitive task analyses (Schraagen, Chipman et al. 2000, Clark, Feldon et al. 2008), which aims to determine what information people need to form correct mental models for task execution.

In order to understand the workflow processes for the old and new fermentors, we embedded a team of researchers in the form of observers with Pfizer personnel overseeing typical clusters of old and new fermentors across two shifts. For the old fermentor shift, a team of 4 observers with no prior experience in fermentation processes but with at least a year's experience in task analyses was split across a 13-hour experiment, broken into two shifts. Two teams of two observers monitored two teams of two Pfizer scientists with more than ten years experience each across the two shifts, who were supervising four fermentors. All four scientists had commensurate levels of experience with the old fermentors. The shift change occurred roughly at the midpoint of the experiment.

Each old fermentor was the same model and roughly the same age. However, as described by the scientists, the machines acted differently based on wear and tear, effectively giving each tank a different "personality" that resulted in some "acting up" more than other tanks. The fermentors were in pairs on a skid, and each skid shared a computer screen used to monitor the vital signs of the experimentation process (e.g., dissolved oxygen, stir rate, pH level). The media under observation was the same in all the new and old tanks.

The new fermentor shift parameters were similar. Instead of four units, two different Pfizer scientists supervised two new fermentors (referred to as Tank 1 and Tank 2), with the entire experiment lasting a little more than 16 hours, with the shift change of the two scientists occurring at roughly the halfway point. As with the old fermentors, two observers monitored the first half of the shift, with two new observers for the second half. One observer in each shift was also present in the previous sets of observations. The two Pfizer scientists had approximately the same amount of experience with the new fermentation units, which was on the order of tens of hours versus the hundreds of hours they had for the old units. The differences between the two observational set-ups are outlined in Table 2.

Both the old and new fermentor units include several control parameters such as pH, DO (dissolved oxygen), temperature, foam alarms, vessel pressure, vessel weight, substrate addition, agitation, constant total airflow and gravimetric feed. One improvement in the new fermentors was the automating of data recording and monitoring, which must be done by scientists supervising the old fermentor.

Foam control is a critical function for all such units, since some foam needs to be present for cell culture growth but too much foam can cause a spill, which is dangerous and ruins a batch. In the older units, humans have to manually inject anti-foam occasionally to keep the foam under control. The new fermentors have automated anti-foam injection capability, but because of a high number of false alarms and related problems, scientists are needed on site for both old and new fermentors.

Both experiments were started in the late afternoon, ran throughout the night, and concluded the following morning. During the experiments, the observers stood to the side and watched the scientists. In addition to the information gained from observing when and what tasks the scientists were performing, often with explanations as to why, additional data was gathered from both scientist- and computer-generated data logs to develop a time-based quantitative analysis of what functions were performed and for how long. When the scientists were not actively engaged with the fermentation units, observers asked questions to increase understanding of the process, pain points, and key activities.

During data collection, all actions by the scientists and the machines were noted, measured to the nearest minute. The time of an event, the duration of the activity, the person or machine executing the action, and any other clarifying notes were recorded. The actions from the machines that were noted were the different alarms that were triggered in response to foaming. During periods of inactivity and at the end of each shift, each team of observers combined their notes and created spreadsheets of tasks, descriptions, times, and other notes. Any discrepancies were resolved between the team members during these time periods, and once resolved, a final spreadsheet was created for each set of observations. The bulk of the discrepancies involved aligning terminology and marking the beginning and end of specific events. There was 100% agreement between the observers in the creation of the final spreadsheet.

Table 2: Parameters for Cognitive Task Observations

Parameter	Old	New
Number of Scientists	4	2
Number of Observers	4	4
Number of Fermentation Units/Scientist	1	1
Shift Time (hours)	13	16
Shift Time Start	4pm	3pm

In keeping with established systems engineering principles (MITRE 2014, INCOSE 2015), we then established the core functions using the data gained from the observations, with validation from management. Once the core functions were determined, we then determined what tasks were subsumed in each function, typical of hierarchical task analyses (Stanton 2006). We then assigned tasks and times to these functions, given the different fermentation units. Our hypothesis was that comparing the functions and task times for operators between the two different fermentation units would allow us to see which functions and task times took the most time, and whether a reduction could be seen given the new fermentation unit.

Results and Discussion

During the two site visits, seven functional groupings of tasks were observed across the old and new fermentors. While individual tasks were not identical between the two fermentor types, they shared common functions, as noted below.

- **Sample** - Any tasks dealing with tank sampling. These actions happened every two hours. Example tasks include taking samples, sample measurement, spraying dispensing valves to cool the tanks, moving samples, analyzing samples underneath the fume hood, bleaching sampling jars, or reinstalling sampling containers.
- **Record** - Any tasks dealing with recording data from the tanks. These occurred every hour and sometimes happened in conjunction with sampling. Examples include hourly paper log recordings, recording of injections, logging key metrics from the tank's digital screen, or entering handwritten log files into the computer.
- **Analysis** – For the old fermentors, the analysis tasks dealt with additional real-time analysis of media from the tanks. Example tasks include gram staining and glucose measurement. These occurred based on pre-existing procedures and did not happen on a regular basis, but at times throughout the experiment. There were no analysis tasks for humans supervising the new fermentors as these were automated in the upgrade.
- **Foaming** - Any tasks dealing with the prevention of tank foaming. Adding an anti-foam agent to prevent excessive foaming occurred on an ad hoc basis in response to visual inspection (looking at the tank) or audio (tank alarm) signals that came from the tank(s). Representative tasks include injecting anti-foam liquid into a tank (~0.5 ml or ~1 ml at a time), proactively filling extra syringes with anti-foam liquid, exchanging syringes, and false alarm inspection and handling.
- **Observe** - Any tasks dealing with the observation of the tanks. These occurred on an ad hoc basis as the scientist(s) observed tank levels and key metrics. Examples tasks include checking tank foaming levels through the side sight glass, reading key metrics from the tank's digital screen, checking trend graphs, and investigating leaking pipes on the tank.
- **Start/End** - Any tasks dealing with the initiation or ending of the experiment. Examples of Start/End tasks include changing the temperature of the media before beginning and ending the cell culture growth process, as well as cleaning the valves and attaching new bottles at the end of the experiment.
- **Other** - Any human tasks not previously captured during the other six functions identified in the fermentation process. These tasks occurred on an ad hoc basis throughout the fermentation experiment. Examples of such tasks include preventative maintenance on a tank, assisting other team(s) in other

experiments, troubleshooting odd tank performance, changing and entering the lab, answering work phone calls, and working on other inactive machines in the lab.

Figure 1 illustrates the workflow of the scientists during their shifts and how each of the functions relates to one another. The analysis function is in gray because it only applies to the old fermentor. The Observe, Sample, and Other functions occur in parallel, which means that scientists periodically move between sampling, observing, and other tasks, depending on the biologic agent and requests for aid from other scientists running different experiments. The dotted line to and from the Other function to the Observe function is noteworthy because often other tasks will occur in a different room, and so this may require scientists to physically leave the room with the fermentation units. Depending on the biologic agent, scientists may have to frequently physically move between these two tasks to check on the foam levels, which can take substantial time.

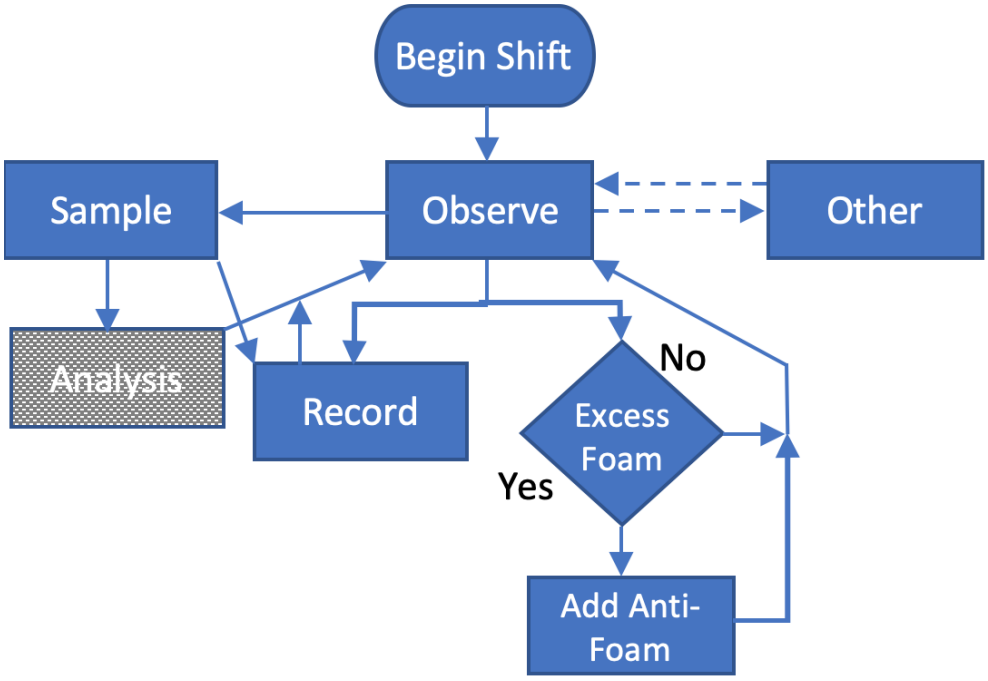

Figure 1: The functional workflow for a typical scientist engaged in laboratory fermentation experiments. The analysis function is in gray because it only applies to the old fermentor. The dotted lines between the Other function and the Observe function indicate that this shift could lead to an operator leaving the room with the fermentation units.

Using the observation and data logs from the two teams of four experimenters assigned to the two different fermentor processes, percent time-per-function graphs were created to demonstrate what percentage of the time scientists (of their total time tasked) spent on the various functions across the two different experiments (Fig. 2). The times on tasks are presented as percentages since as noted in Table 2, the experiments were of different lengths.

Between the two different experiments, the percent time spent on starting/ending an experiment and recording data were fairly consistent, analysis and sampling took much longer in the old system, and observing and managing foaming taking longer with the new system. Given the total shift times from Table 2, scientists interacting with the old fermentors were actively tasked in managing them for 51% (6.66 hrs/13hrs) of their shift, with the new fermentor scientists actively tasked for 34% (5.45 hrs/16 hrs) of the time. Thus, there was a 17% overall reduction in workload with the new system, although the reduction was not uniform across functionalities.

Figure 2, which breaks down the percentage of time spent on the different functions per either the 6.66 hrs or the 5.45 hrs of active tasking, clearly illustrates that the removal of the entire function of analysis contributed to the overall drop in task load for the new fermentor. Because automation could reliably and accurately replace scientists for this function in the new fermentors, scientists were freed from this task and could concentrate on other areas of need. Indeed, this investment was the primary driver in the overall ~17% reduction in scientist workload. The other major reduction in workload occurred in the sampling function. The upgrade to the new technology resulted in a large reduction in sampling work by 57%. However, Fig. 2 also demonstrates that adding automation in system upgrades may not always result in reduced workload. The foaming tasks, especially those involving injecting anti-foam, and the amount of time required to observe the cell culture growth process increased for the new fermentors.

The increased observation time could be attributed to the newness of the equipment, which had only been in place for a few months. When the Pfizer management team was presented with the results, they suggested that operators may have been adjusting their strategies in learning to use the new system. However, the almost doubling of the new fermentor anti-foam activity, despite the fact that only two tanks were under observation instead of 4, highlights the difficulties surrounding foam control in fermentation units. Despite the new system with improved sensing, foam control required more, not less, attention.

Foam management is notoriously difficult (Junker 2007, Routledge 2012), especially in relatively smaller fermentation R&D reactors with the microbial culture solutions generating unpredictable foaming in the tank. This poses a problem because if the foam is left untreated, the potentially lethal pathogen may "foam out," which means the foam spills out of the top vents of the system. This leads to exposed personnel to the pathogens and an expensive loss of the entire batch. As described by one scientist, "If we lose a run, work for a total of four weeks is lost. Many others depend on the data we produce."

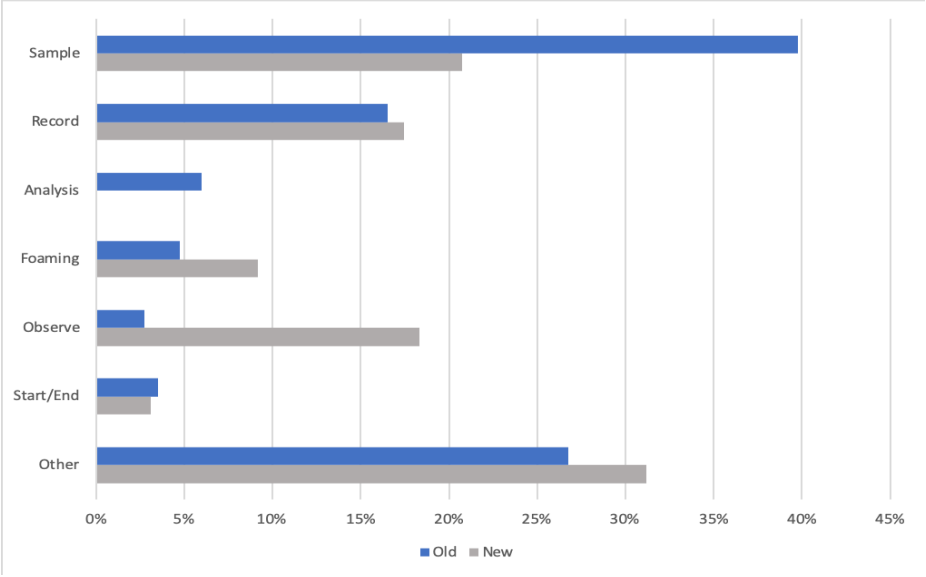

Figure 2: Percent of active tasking time (6.66 hrs for the old and 5.45 hrs for the new) scientists spent on seven functions for old and new research and development fermentors.

To prevent such a "foam out," scientists monitor the microbial culture in order to manually administer an anti-foam solution. The foaming process is currently unpredictable and a delicate balance is required in introducing just the right amount of anti-foam agent to prevent an expensive and potentially hazardous foam-out, while avoiding high anti-foam concentrations which can inhibit cell growth. This control loop currently cannot replace the human capability to judge the appropriate timing and volume of anti-foam required in such settings, which is why the role of the human is still quite important.

This functional analysis showed that foam control for the new fermentors took more time than for the old fermentors relative to active tasking time. One significant limitation of this analysis is that it is

based on only observing a single experiment for the new and old fermentation units. While ideally more observations across a wider range of conditions would be preferable, these two experiments were representative of typical runs, so they provide utility in understanding routine work flow processes in research vaccine development.

The next section will discuss how such functional analyses can aid in diagnosing problems and identifying possible mitigations.

Functional Analyses as Diagnostic Tools

Human-machine functional analyses can be especially useful in investigating the nature and variability of various processes in order to gain insight into potential solutions, both from a technological but also a workflow development perspective. Using the new fermentor as an example since the old units are being phased out, Fig. 3 shows the number and categories of tasks associated with each function over the 16-hour shift of the new fermentor process. One interesting observation from Fig. 3 is that the amount of time scientists spent observing the process decreases over time and by 3am, scientists do not dedicate any more cognitive resources to this task. However, the foaming actions were relatively consistent, meaning that the system required several anti-foam injections from the 3am-7am window. So the system needed attention, which it received, but operators were not as attentive as they had been in the earlier part of the shift.

Performance issues with people's circadian rhythms on overnight shifts have been well established (Kazemi, Haidarimoghadam et al. 2016, Chellappa, Morris et al. 2019) and this, coupled with people's inability to sustain attention in monitoring tasks for long periods of time (Shaw, Matthews et al. 2010), suggests that this system would benefit from better alerting or perhaps a computer-vision monitoring system that can augment human supervision in these difficult periods. Work is currently underway to address these possible technical interventions.

Another important inference from Fig. 3 is that there is time spent in the "others" function, every hour, which primarily consists of scientists helping other scientists on different experiments. These are frequent and time-varying organic tasks without any formal requirements. While management knew such collaborations existed, this analysis was the first to formalize the extent of such cross-experiment assistance,

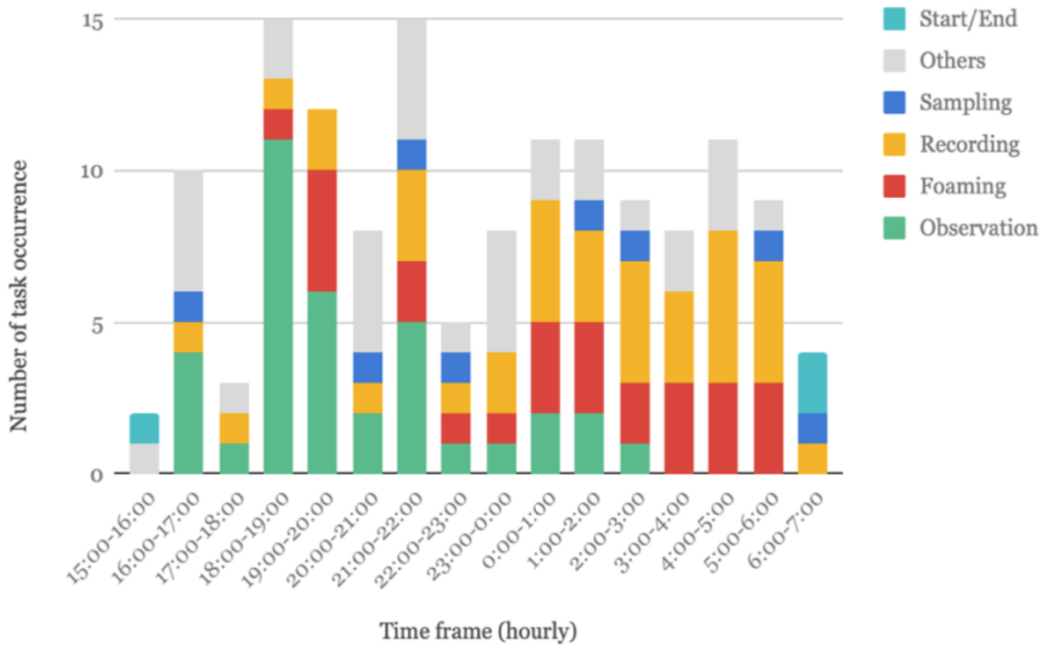

Figure 3: Number of tasks per hour spent across the combined six functions for the two new tanks.

which was more than expected. Such opportunistic and unplanned collaborations can be very beneficial not just for the team of scientists who need help, but also to those scientists working the overnight shift who may be struggling with fatigue, which is common in such settings (Richter, Acker et al. 2016).

Given the dynamic and organic nature of such unplanned collaborations, individual scientists would likely benefit from remote monitoring capabilities for observing fermentation units. Such tools could alert responsible scientists when foam alerts occur or when processes and tanks exhibit anomalous behavior. This kind of tool would allow scientists to meet these unplanned requests while also ensuring safe operation of the fermentation tanks. To this end, a user-initiated notification (Guerlain and Bullemer 1996) application has been built that allows scientists to be mobile and also visually watch up to 4 units at one time. Implementation and testing is underway.

The functions-by-time graph in Fig. 3 also provides insight into the number of anti-foam management tasks that occurred overtime under the "Foaming" function. The number of anti-foam injections needed to control foam growth were inconsistent in frequency in the first half of the shift, but then became more regular in the last seven hours of the shift. To better understand the underlying issues surrounding such events, this function allocation analysis can also be used to drill down into those specific anti-foam tasks to determine when and which tank under observation is causing the majority of the problems, as seen in Fig. 4.

Recall that for the new fermentor operations, there were two tanks under observation. A task decomposition of the anti-foam management function that specifically looked at the injection of anti-foam revealed differences in foam management across the tanks (Fig. 4). Even though the tanks were acquired and installed at the same time and contained the same cell culture with the same initialization parameters, Fig. 4 clearly shows the different operational behavior in two different tanks. Tank 2 required almost half the number of anti-foam injections, resulting in a significantly less total amount of anti-foam being added. Such differences lead to scientists ascribing different "personalities" to each tank and influence how individuals build mental models of strategies needed to deal with anomalies.

Figure 4 further illustrates how unpredictable foaming can be and why a human is currently needed to supervise such a process. This lack of consistency in tasking demands is also captured in Fig, 3. Such uneven demands are typical of not only manufacturing processes, but also in other areas of

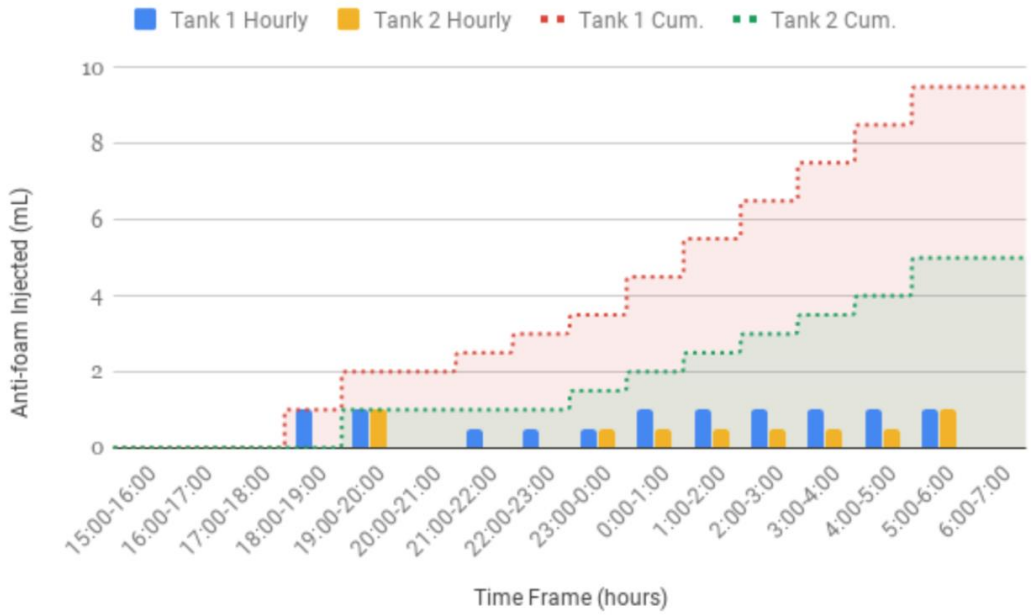

Figure 4: Anti-foam injections in the two new tanks over the 16 hr shift both hourly (represented by bars) and cumulative (represented by the dotted lines).

automation supervision like flying. Supervision of process control automation and other highly automated systems often comes with long periods of very little to do, punctuated with occasional time- and safety-critical tasks like the insertion of anti-foam. These irregular and often stochastic temporal features can make staffing difficult, since enough people must be on site for the worst-possible outcomes, but then this often leaves many people struggling to stay engaged in periods of low task load. Ideally, joint human-automation systems would be designed to develop more predictable task loading over time. To this end, work is currently underway to determine whether a machine learning approach can provide more accurate foaming predictions for use in a closed-loop feedback system, and thus make scientist task loading more predictable.

Conclusions

Inserting automation into manufacturing processes in R&D laboratories like that of vaccine fermentation can reduce output variability and improve efficiency and safety. However, a process often cannot be fully automated, and because of the need for systems with partial human interaction, it is not always obvious how and to what extent partial automation produces the intended benefit. To this end, we demonstrated how a functional analysis that examines when and what functions and tasks humans supervise can provide critical and descriptive efficiency and workflow information.

In examining the upgrade from old to new fermentors, this analysis showed that the new model removed the need for humans to do the analysis function and also significantly reduced the effort need across sampling tasks. However, as is often the case, while the addition of a new system had the net effect of reducing workload, this was not true across all functions. The new system actually increased the task load across the observation and foaming functions. Once the team has become more familiar with this system, a similar follow-on analysis might reveal a workload reduction and if not, then the analysis could indicate if there is a deeper problem that should be addressed.

This case study also highlighted that the use of functional analysis could be diagnostic and help reveal possible problem areas and potential mitigation strategies. This analysis revealed that significant collaboration is happening across experiments with different groups of people who often require assistance. This discovery suggests that more can be done to optimize workload and scheduling. In addition, as shown through the anti-foaming analysis, it was clear that despite being almost identical, the new fermentors demonstrated different behavior, so this information can now be used to develop better foam mitigation strategies, including assisting in the development of a more accurate control system.

Two scientists working across two shifts with the older fermentors interacted with the fermentors for 51% of their shifts. As intended with the introduction of the two new fermentors, this same overall time spent interacting with the fermentors dropped by 17% to 34%. This workload reduction allows scientists the ability to spend less time on repetitive tasks and more time concentrating on other, more open-ended activities such as study design and data interpretation from experiments that require more expertise. This functional assessment is important after the installation of new equipment to ensure that the system had the intended effect of reducing workload. However, while there was an overall reduction in workload, some tasks with the new system required more effort, which was not expected.

Such a reduction in time spent by scientists actively supervising equipment would appear to be a positive benefit, but it could have the exact opposite effect. Previous research has shown that human performance is more likely to degrade when tasking is below 30% and above 70% (Rouse 1983, Donmez, Nehme et al. 2010, Cummings, Mastracchio et al. 2013). When tasked over 70%, people may have too much to do and often make mistakes, but when tasked less than 30%, they can become bored, leading to distraction and decreased job satisfaction (Cummings and Gao 2016).

While in this particular case study the scientists using the new fermentor units are tasked slightly above the 30% threshold of their overall shift time, it is likely that as they get more familiar with the system, time spent actively supervising the fermentors could decrease. As the system becomes more autonomous, it will become increasingly important to ensure scientists' time is effectively reallocated to cognitively-engaging activities and tasks.

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