Understanding the Influence of Robot Motion on the Experimental Processes Present in Food Science Applications

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***Abstract*— Laboratory experiments in modern food labs are human-driven and tedious processes which can have limited throughput, reliability, repeatability or robustness. Through repeatable motions and precise control of process parameters, robotic automation can provide significant improvements to the existing experimental processes, and also improve manual assessment of the sensory data. By developing a robotic automation system which performs the make, measure, adjust and clean processes for a milk beverage made from water and powdered milk, we explore how variation in different process parameters impacts quality of the beverage in terms of the measured pH value. Using collected data we also identify optimal process parameters from robustness and time-cost standpoint. By comparing performance of the robotic system to a human we demonstrate varied performance in the pH adjustment process and 3x better precision in the pH probe cleaning. We identify that designed robotic system requires 45% more time to perform the experiment when compared to a human, yet provides significant advances in terms of repeatability and reproducibility. These findings demonstrate feasibility and benefits of the robotic automation in the food lab environments, thus paving the way for the broader implementation.**

I. INTRODUCTION

Plant-based diet and food products represent a core part of sustainable development policies [1]-[2]. Faced with aggressive sustainability targets and coupled with change in consumer preferences, the food industry is currently experiencing a shift towards plant-based food products [3]. Development and optimization of such products is first performed in food labs where many of the processes are manual, which is time consuming and labor intensive [4]. The experimentation process typically involves mixing of ingredients, homogenization and pasteurization which is followed by measurements and analysis [5]-[6]. The limited throughput restricts data collection whose method is often ad-hoc, limiting the accuracy and repeatability of the results [7]. These challenges severely slow the development of new food products, especially plant-based ones, since they involve partially explored raw materials. Utilizing robots to automate such processes could improve not only food manufacturing [8]-[9], but also design and experimentation [10]-[11].

Lab automation is a rapidly growing research area with many notable successes. A mobile robotic platform has been deployed in a chemistry lab to perform experiments and identify optimal photocatalyst for hydrogen production using optimization methods [12]. Separate works have explored the synthesis of organic compounds using robotic arms [13], however, these robots are optimized for interacting with a specific environment for a specific task [14]-[15]. Despite

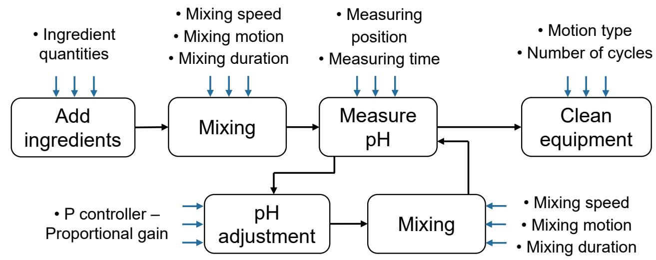

Fig. 1. Beverage formulation process performed by the robotic system.

these advances there has been limited demonstration of robotic automation applied to food science. The experiments in food science are typically larger in scale, last longer, are prone to change and are performed in unstructured environments. In comparison to chemistry labs, food science does not typically use standardized well plates, but use a variety of beakers and devices, requiring more adaptable manipulators. Existing work within the food science domain includes a robotic system which uses human taste for omelette recipe optimization [16] and a salinity sensor for further food flavor exploration [17]-[18]. Within the beverage domain, robotic pouring is used for the assessment of beer quality [19], analysis of wine quality through foam formation [20] and evaluation of carbonated water [21]. These robotic systems demonstrate the advantages and potential of applying robots to these scenarios, however there has been limited exploration of how robots can aid food science experiments.

In order to explore the potential of robotic manipulation for food science experimentation, we propose a robotic setup which can automate the preparation, pH measurement, pH adjustment and cleaning processes to obtain beverage formulation. Long term this could be used to study and develop plant-based food products, however, currently we use it for a test case of a milk-powder model beverage. Key to this process is the use of a pH sensor to analyze the beverage. We explore how a robot can use pH readings to assess repeatability of robotic experiments, quantify how the change in process parameters impacts the experiment, perform pH adjustment and optimize the cleaning process. Furthermore, we utilize pH sensing in conjunction with the precise motion control offered by robots to optimize and characterize the experimental process. We compare the optimized robotic experimental process to the process completed by a human, in terms of time and pH readings. Our findings show that robot matches or exceeds human capabilities for pH measurement and adjustment. The sensor cleaning process takes 2.5x more time for the robot but exhibits on average 3x cleaner results.

In the remainder of the paper we first introduce the methods used to investigate how process parameters like mixing time, speed or pH measurement position impact measured pH value, and also give details of the methods for pH adjustment. Furthermore, we provide details of the robotic implementation, before providing the experimental results and conclude with a discussion on the robots performance.

II. METHODS

A. Problem Statement

The standardized process of beverage formulation is composed of preparation, measuring, adjustment and cleaning steps as summarized in Fig. 1. The ingredients must be combined and mixed to achieve a homogenous solution. pH adjustment is then performed for improvement of the stability of the liquid. Finally, the pH sensor must be cleaned to allow the next experiment to proceed.

We explore how robotic automation and pH sensing can improve our understanding of the experimental process and improve its reliability and efficiency. To evaluate this, we consider a simplified model beverage formed from milk powder and water, where the pH is adjusted with acid. The ingredient ratio varies across the experiments, between 10%-30% of milk powder by weight. A robotic manipulation system has been designed to prepare the beverage, measure pH using a pH probe, adjust pH using custom syringe pump and clean the pH probe using a custom cleaning setup.

B. pH Readings

pH is a measure of the hydrogen ion activity and provides insight into acidity and alkalinity of the analyzed solution [22]. The pH of a beverage is important as it affects its stability, shelf life, sensory properties and thus must be adjusted to a required set-point. However, the pH of the solution is also affected by numerous factors during the experiment - i.e. mixing, dispersion and hydration of molecules, thus indicating that pH as a metric can be used to understand, assess and optimize the experimental process.

C. pH for process optimization

We propose that by using the robot to measure the pH in different points of the container during model beverage preparation process, we can understand the mixing behavior of the powder in the liquid, adjust the pH and identify when the pH sensor is sufficiently clean. We now describe the different modes of using the pH to understand and optimize the experimental process.

1) Settling time: When exposed to a stimuli a pH probe takes time to settle to the nominal value. Typically a human may wait for a given period, leading to either unnecessarily long waiting periods, or inaccurate measurements. Using automated and continuous capture with a robot we propose finding the appropriate settling time by considering the rate of change between pH readings. When this rate of change is below a given threshold, the measurement can be described to be static, thus condition for settling is given by $|pH_{t+1} - pH_t| < pH\ measure\ threshold$, where $pH\,measure\,threshold$ is the tolerance defined by relevant industry standards and practices.

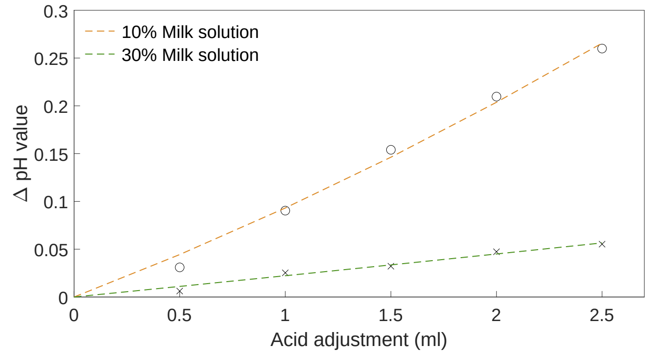

Fig. 2. Proportional controller pH adjustment calibration curves for the 10% and 30% milk solutions.

2) Robot Mixing Motion: For some solutions which are not fully homogeneous, the pH may vary across the solution, so sampling at one point may not return an accurate result. The robot can accurately and repeatedly sample the pH at different locations across the liquid and identify changes in the pH to assess mixing effectiveness.

3) Robot Mixing Duration: Change in the measured pH is explored for the variation in mixing duration, while keeping constant RPM and mixer motion pattern. Longer mixing leads to more homogeneous solutions, prompting investigation into the impact of mixing duration on the pH.

4) pH Cleaning: Residual liquids, particles and foam affect accuracy of pH measurements. A pH probe is manually cleaned after each experiment by spraying distilled water onto the probe until residue is visually removed. We propose that by using a pH probe to measure the pH of a known cleaning liquid, we can use the error between the known pH and the measured one to identify if the probe is sufficiently clean as $|pH_{measured} - pH_{known}| < pH\ clean\ threshold$, where $pH\ clean\ threshold$ is the tolerance defined by industry standards and practices.

Cleaning of the pH probe is essential to the reliability of the pH measurement process, but verification of clean state with pH measurements is time consuming. Robotic automation can achieve a balance between cleanliness and process duration with repeatable motions and set number of cleaning cycles, independent of the measured pH. In this case, the optimal cleaning procedure must be identified beforehand using both pH readings and visual feedback.

D. Closed-Loop pH Adjustment

Adjusting the pH to the desired value is an essential step in the beverage formulation process. We propose using a proportional controller to add sufficient acid to lower the pH in order to reach the target pH value. The proportional controller k_p parameter is dependent on the milk concentration. As seen on Fig. 2, the change in the pH with volume of added acid is linear, however the gradient varies with the concentration of the milk mix. By obtaining k_p values for both minimum and maximum of range of solution concentrations, the k_p value can be dynamically tuned within this range. The implemented controller has the form:

$$\Delta v = \alpha(pH_{measured} - pH_{target}) \quad (1)$$

where Δv is the volume of acid added for pH adjustment, α is dynamically controlled tuning parameter which is based on the solution concentration, $pH_{measured}$ is the starting pH, and pH_{target} is pre-defined.

In order not to exceed target pH value, α is initially set at α_0, which is defined using the calibration curve for the 10% milk solution as $k_{p(min)}$ parameter. Additionally, in this initial adjustment step, 90% of the calculated adjustment liquid is dispersed ($\alpha_0 = 0.9k_{p(min)}$), while every subsequent pH adjustment iteration adds 100% of the calculated amount. This is followed by an iterative adjustment period where α is adapted to α_n for each adjustment step n according to:

$$\alpha_n = \frac{\sum_{n=1}^{n-1} \Delta v}{|pH_0 - pH_{n-1}|} \quad (2)$$

This allows for dynamic change of the adjustment rate and thus precise pH adjustment for different solution concentrations. Here n denotes number of adjustment steps, $\sum \Delta v$ represents total volume of the adjustment liquid added.

Inadequate dispersion of the acid can lead to a small or no change in the measured pH, leading to a rapid rise in k_p and thus a lower pH than the target, requiring repeat of the entire experiment. To prevent this behavior, α_n is kept within the range $k_{p(min)} \geq \alpha_n \leq k_{p(max)}$, where α_{min} is defined using $k_{p(min)}$ parameter derived from the calibration curve for 10% solution and α_{max} is defined using $k_{p(max)}$ parameter derived from the calibration curve for 30% solution.

III. EXPERIMENTAL SETUP

An experimental setup has been created to automate the process and explore the role of the pH sensor. The setup (Fig. 3) uses a UR5 6 DoF Robot Arm, high shear mixer, pH probe (DFRobot Meter Pro Kit V2), custom syringe pump and cleaning system. The ingredients are pre-dosed into the measuring cups which are manipulated using custom gripper mounted on the robot arm. Necessary robot arm motion paths are performed through a number of set waypoints.

The gripper uses a rack-and-pinion mechanism connected to a DC motor in order to move the silicone padded fingers while current feedback and a fixed threshold robustly detect when cups are grasped. Additionally, a linear potentiometer prevents out of range motion by providing finger position information. The gripper enables cups to be moved around the workspace to access the mixer and pH probe. The speed of the mixer can be set, and controlled automatically. To adjust the pH, a custom syringe pump actuated by a stepper motor allows dosing of acid, while tube attached to the syringe enables smaller droplet size and thus higher dosing precision. The cleaning system uses a ‘cleaning cup’ with two tubes connected to a pump to spray fresh water onto the probe. Waste water is collected in the cup which can be emptied, enabling contamination-free process repeatability.

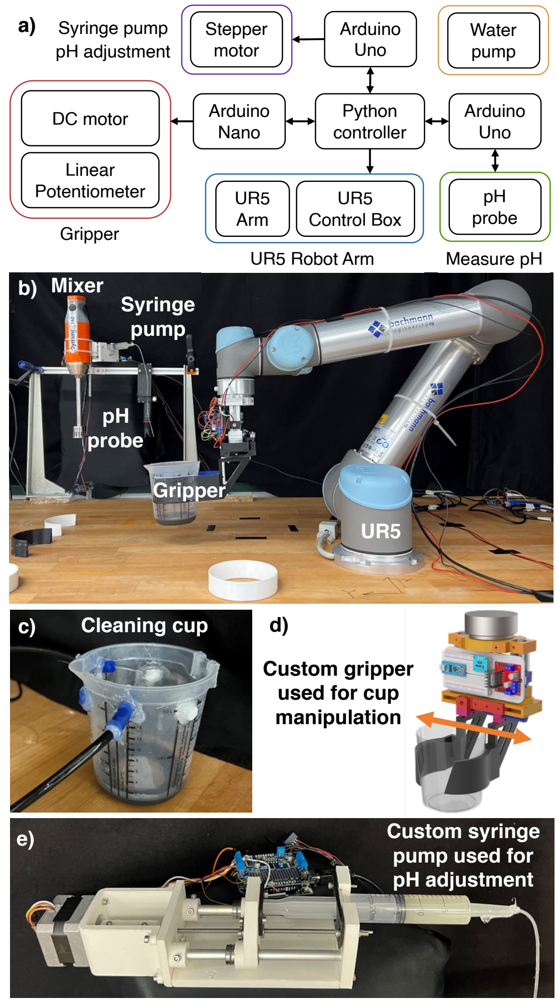

Fig. 3. Overview of the experimental setup. **a)** Diagram of the control architecture. **b)** Experimental setup equipment. **c)** Cleaning cup with two nozzles which spray fresh water to clean the pH probe. **d)** Custom gripper used for manipulation of cups which contain either ingredients or mixed solution. **e)** Syringe pump used for the pH adjustment.

A. Experimental Process

Experiments were performed with 10% and 30% powdered milk weight solutions in 500 ml cups with total weight fixed at 400 g. The mixer speed was set to 5000 RPM for the 10% solution, and 7000 RPM for the 30% solution. Temperature effects are considered negligible, since all experiments were performed in succession. All experiments were performed with the non-calibrated pH probe.

Experimental process with its parameters is shown on Fig. 4. Measuring cups with pre-dosed ingredients are placed in known locations in the workspace of the robot. The robot pours the ingredients into mixing cup and then performs the mixing process for a given time and mixer speed. During mixing process, the robot arm moves the mixing cup in predefined motion around the mixer head with goal of achieving homogeneous solution. After mixing, robot moves the cup to the pH probe in order to perform pH measurement for a given time. pH adjustment is then performed using concentrated lemon juice which is mixed for 5 seconds to ensure even distribution across the solution. pH is measured again and

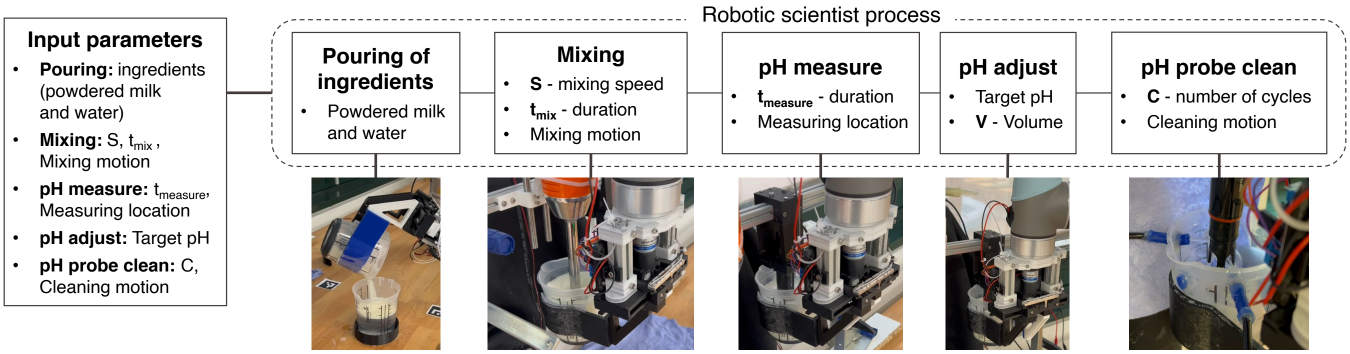

Fig. 4. Step by step visual illustration of the experimental process represented alongside controllable parameters.

the process is repeated until target pH is reached. The robot then returns the mixing cup and picks up a cleaning cup to clean the pH probe using a predefined motion pattern for a set number of cycles. Waste water from the cleaning process is poured into the separate container and cleaning cup is returned, completing the whole experimental process.

IV. Experimental Optimization

In this section we analyze how variation in process parameters impacts the pH of the 10% and 30% solutions. For the pH measurement process we identify its optimal duration while trying to achieve balance between robustness and time efficiency. Additionally, we demonstrate change in measured pH when performing pH measurements at different locations across the liquid. We conclude this section by demonstrating how the change in mixing duration impacts measured pH.

A. pH measuring duration

As illustrated on Fig. 5, pH measurements for both milk solutions stabilize within tolerance limits around 20s, with minor changes until 30s. Using this information, the optimized duration of pH measurement process is 20-25s for the short process and at least 30s for the robust process. This experiment shows that pH data can be leveraged for the identification of the ideal pH measurement duration, irrespective of the type of the pH probe or solution itself.

B. Measuring pH at different locations

Measuring pH at different locations across the liquid provides insight into solution homogeneity and thus information whether additional mixing is required or not. Higher variation in measured pH is experienced with more viscous solutions as visible on Fig. 6. When compared to a measurement at a single point in the center, maximum change of 0.006 and 0.013 for the 10% and 30% solutions is observed. This result is within the tolerance limits of ±0.03, leading to the conclusion that analyzed solution is well mixed.

C. Mixing duration

Significant increase in measured pH has been observed for both solutions for longer mixing durations, as visible on Fig. 7. Despite the difference in the curve gradient, both solutions experience rapid change in the measured pH until 90s. The less viscous 10% solution continues this trend, while

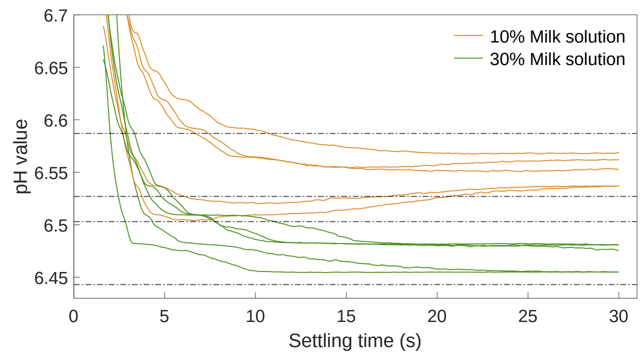

Fig. 5. Stabilization of pH readings in homogenous 10% and 30% milk solutions, tolerance limit of ±0.03 from mean is used as a boundary.

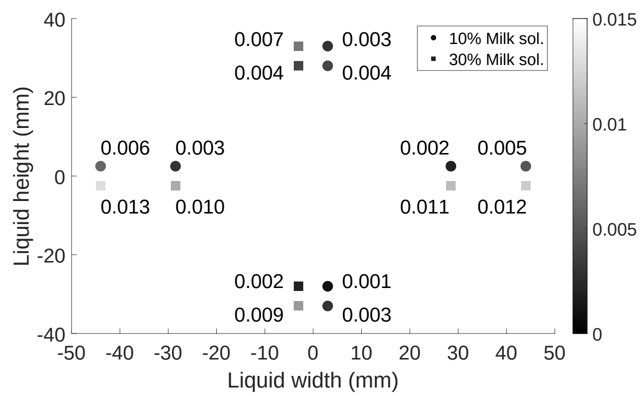

Fig. 6. The variation in measured pH when measurement is performed at different locations in the liquid.

30% solution beyond this point experiences slight change in the pH. The widest error range in the pH is observed for the 30% solution at 60s, but it significantly decreases for all subsequent measurements. Less dense 10% solution has close to identical error range across all experiments.

V. Experimental Results

Within this section we assess the accuracy and precision of the pH adjustment process for two solutions and three target pH values. We also analyze the pH probe cleaning process using pH measurements and visual feedback and identify the optimal cleaning cycle for robustness and time efficiency. Finally, we compare performance of the robot and human in terms of accuracy, precision and time duration.

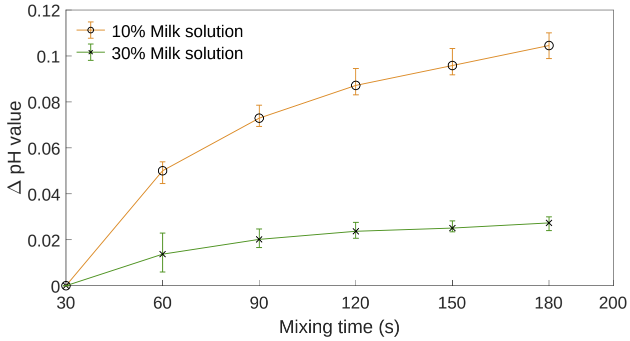

Fig. 7. Change and variation in the measured pH for different mixing durations for 10% and 30% milk solutions.

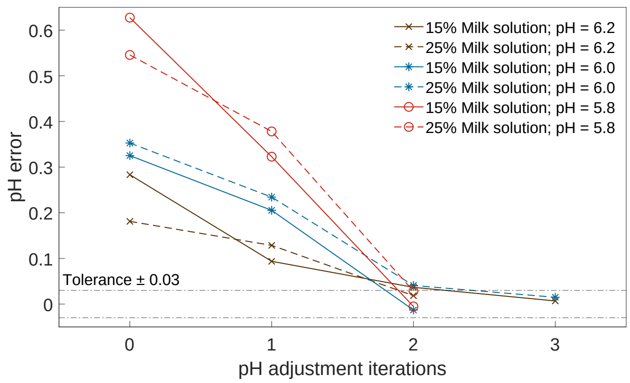

Fig. 8. Proportional controller performance for 15% and 25% mik solutions and three target pH values.

A. pH Adjustment

The tuned proportional controller was tested on intermediate 15% and 25% milk powder weight solutions for three different target pH values as illustrated in Fig. 8. Approximately linear pH adjustment behavior is identified for all conducted experiments, with the target pH value reached in two or three adjustment steps. Higher accuracy is observed for the 15% solution, while the adjusted pH of the 25% solution is on the very edge of the tolerance field.

B. pH Probe Cleaning

The cleaning process was tested on 10% and 30% milk solutions for up to three cleaning cycles in situations when the pH probe was cleaned immediately and when residual liquids were left to dry on the pH probe for 30 minutes.

The cleaning experiments were assessed visually and by pH measurements as illustrated on Fig. 9. It was observed that pH error measured in reference to the pH of the cleaning liquid is smaller with the higher number of cleaning cycles. Visually, one cleaning cycle was robust enough to remove all residual liquids and leftover foam, with highest error reduction observed in first and second cleaning cycle. For delayed cleaning, the first cleaning cycle left some residual milk which was removed by the second cleaning cycle, occasionally causing a slight rise in pH error. Third cleaning cycle does not show visual benefits, but from the pH readings it was observed that pH probe gets cleaner thanks to the longer interaction between clean water and the pH probe.

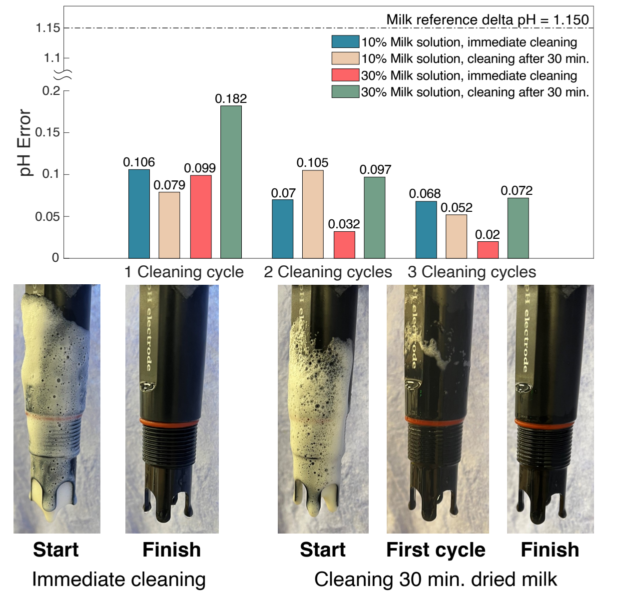

Fig. 9. pH probe cleaning performance utilizing the robotic setup. Top figure shows measured pH error with reference to the pH of a cleaning liquid for up to three cleaning cycles, analyzed for 10% and 30% milk solutions. pH probe is cleaned either immediately or after 30 minutes. Bottom figures represent visual cleaning performance for wet and dried milk.

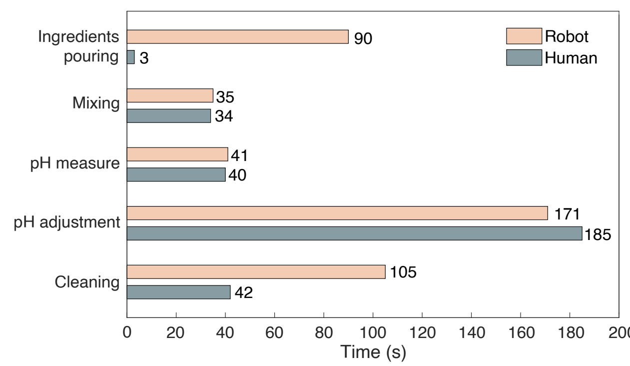

Fig. 10. Comparison of a human and the robotic system in terms of the time required for completion of the tasks in the beverage formulation process.

The experiments show that by measuring pH during the cleaning process it can be detected if the pH probe is being cleaned. However, due to long long settling times required for accurate pH readings, this approach is impractical. By combining pH data from the cleaning experiments with visual feedback, optimal cleaning cycles can be identified. The analyzed food system requires one cleaning cycle for wet milk and two cycles for dried milk.

C. Human-Robot Benchmark

A comparison between robot and human was performed for the experimental process illustrated on Fig. 10. The experiments differ in the pH adjustment step since human manually identifies the amount of acid to be added. Additional difference exists in the pH probe cleaning step since robot utilizes custom cleaning equipment while human uses spray bottle. Human performing the experiment is well-rested, untrained and has no experience with the experiment.

As seen in Table I, both human and robot show varied pH adjustment performance. The cleaning comparison between robot and human presented in Table II shows that robot has 3x smaller pH error when compared to a human. However, time-wise human is almost 45% faster as illustrated on Fig. 10. Superior human dexterity shows benefits in motion heavy tasks like cleaning and pouring of ingredients with respectively 2.5x and 30x shorter task duration. Identical human and robot performance is observed in mixing and pH measurement tasks since they have fixed duration. Similar performance in the pH adjustment process is tied to the fixed duration of the pH measurements. In this task human has advantage in motion activities while the robot is faster in calculation and dispersion of the pH adjustment liquid.

	Human		**Robot**	
	15% sol.	**25% sol.**	**15% sol.**	**25% sol.**
Adj. iterations	3	2	2	3
pH error	0.23%	0.06%	0.11%	0.29%

TABLE I

HUMAN-ROBOT PH ADJUSTMENT PERFORMANCE.

	Human error		**Robot error**	
	10% sol.	**30% sol.**	**10% sol.**	**30% sol.**
Immediate clean	0.78%	3.28%	0.63%	0.26%
Delayed clean	1.12%	4.12%	0.67%	0.93%

TABLE II

HUMAN-ROBOT PH PROBE CLEANING PERFORMANCE

VI. DISCUSSIONS & CONCLUSIONS

Within this paper we introduce the concept of the robot automation in the food labs, for the task of beverage preparation and assessment. We present a robotic platform that can prepare beverages from powdered milk and water, measure pH, perform pH adjustment and pH probe cleaning. A robotic approach to the experimentation allows quantification of the impact of process parameters to the measured pH. It was observed that change in mixing duration leads to huge discrepancies in pH, while measuring pH in different locations in the liquid has negligible effects. We also demonstrated that robot can clean the pH probe reliably and perform pH adjustment. The robot and human show varying precision in pH adjustment while robot outperforms human in cleaning task. However, the robot is slower, taking 45% more time, but it can operate continuously and thus free up human scientists.

This work could be extended to combine robotic automation and learning methods for the optimization of the food formulas. By utilizing methods such as Bayesian Optimization, the robot could efficiently explore the design space and optimize formulations and processes. This approach should be demonstrated on more complex food systems, trying to achieve a target viscosity, pH or other relevant metric. In addition, beverage assessment should be enhanced with additional sensors measuring viscosity, conductivity, color and beverage stability. This would further exploit robotic automation to gather data in a reliable and repeatable manner.

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