Digitalizing Slurry Mixing for an Electrode Manufacturing SDLs

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1. Introduction

The slurry mixing and coating process is a key step in determining the microstructure and final performance of electrode. Conventional manual procedures suffer from high variability and low reproducibility, creating a critical bottleneck for data reliability in AI-driven material discovery. To address this, we propose a Self-Driving Laboratories (SDLs) framework that automates the entire process from mixing to electrode fabrication. A core foundational step of this infrastructure is the development of Planetary Mixer Control Library (PMCL), a specialized Python-based API for the precision control and real-time monitoring of planetary mixers. By analyzing serial communication protocols, PMCL transforms physical mixing cycles into reproducible digital assets, establishing the high-fidelity data backbone necessary for future closed-loop optimization and autonomous manufacturing.

2. Backgrounds

Electrode manufacturing is a multi-stage process where the slurry mixing and coating phases are paramount in determining the final electrochemical performance. Unlike simple chemical solutions, battery slurries are complex mixtures governed by non-Newtonian rheology, making them highly sensitive to physical processing parameters such as mixing speed, duration, and shear rates.

Current manufacturing practices predominantly rely on manual protocols, which introduces significant human-induced variability and limits reproducibility. This lack of standardization creates a "digital gap" in data collection, posing a major hurdle for AI-driven material discovery that requires high-fidelity, consistent datasets. Consequently, establishing a digital infrastructure capable of capturing the intricate physical cycles of high-viscosity mixing is a critical prerequisite for the realization of autonomous manufacturing.

2.1 Related work

The paradigm of SDLs has fundamentally shifted materials research toward autonomous, closed-loop discovery by integrating modular robotics with AI-driven orchestration [1]. Significant milestones in this field include the development of mobile robotic chemists capable of navigating unstructured laboratory environments to automate researcher-level operations [2], and the realization of fully automated inorganic synthesis platforms, such as the A-Lab, for accelerated material realization [3].

In the specific context of energy storage, pioneering efforts have demonstrated the autonomous optimization of liquid electrolyte formulations through machine learning-coupled robotic test-stands [4]. However, these existing systems are primarily optimized for liquid-phase pipetting or solid-state powder handling. The unique orchestration challenges posed by the transition from powder precursors to high-quality coatings—specifically involving high-viscosity mixing and precise blade coating—remain largely underexplored in current SDL paradigms. This work addresses this gap by focusing on the digitalization of these complex physical manufacturing stages.

3. System Implementation and Methodology

Our implementation establishes a robust digital-physical bridge for electrode manufacturing, addressing the critical "data gap" in slurry processing. The system architecture is designed around two primary pillars enabled by the Planetary Mixer Control Library (PMCL).

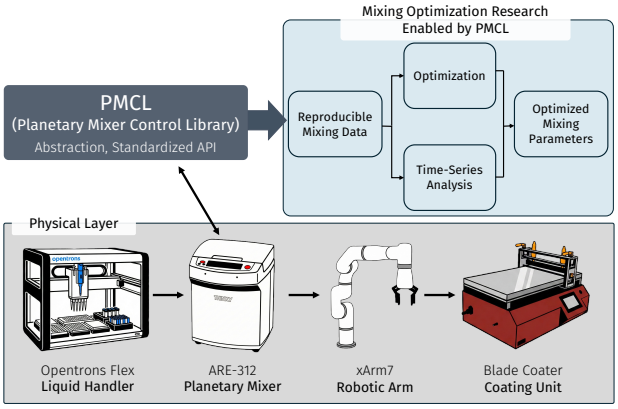

Fig. 1: Schematic of the proposed SDLs framework: Digitalizing planetary mixing via PMCL and orchestrating robotic transport for autonomous electrode manufacturing.

First, PMCL serves as a specialized software-defined bridge between industrial mixing hardware and the digital orchestration layer. The library allows for direct, programmatic control that bypasses the limitations of manual operation. This digital-physical interfacing is the essential first step in transforming a legacy hardware unit into an AI-ready experimentation platform.

Second, the framework ensures high-fidelity data integrity by transforming physical cycles into reproducible digital assets. Unlike conventional methods where mixing parameters are often manually transcribed, PMCL enables real-time logging of rotational

speed and operational duration at high sampling rates. These logs serve as immutable digital twins of the physical mixing process, providing the "soundness" and reproducibility required for training next-generation optimization models.

The current hardware loop integrates an xArm7 robotic manipulator and an Opentrons Flex to provide a standardized physical environment for these digital assets. By automating sample transport and liquid handling, we minimize human-induced noise, ensuring that the high-fidelity data captured by PMCL remains consistent throughout the entire manufacturing pipeline. This integrated setup provides the necessary data backbone for future closed-loop modules, including real-time rheological calculations and autonomous formulation discovery.

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