Modelling and Control of Slot-Die Coating in Battery Electrode Manufacturing

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Motivation and challenges

Lithium-ion batteries (LIBs) are key to achieving **global net zero** by 2050. Electrode manufacturing is among the most expensive stages of LIB production and remains largely optimised through **trial and error**. Slot-die coating is a key step in electrode manufacturing—improved thickness uniformity and consistency could reduce manufacturing costs while increasing cell performance, yield, and process repeatability. Achieving this requires **closed-loop control**, yet several challenges remain:

- **Modelling:** the coating process is governed by multiphase PDEs, making CFD simulations too computationally expensive for control design & real-time operation.
- **Automation:** current battery manufacturing lines remain only partially automated, with many process parameters still adjusted manually.
- **Metrology:** online sensors are not designed for feedback control and are poorly characterised, while the relationship between manufacturing measurements and final cell performance remains an active research topic.

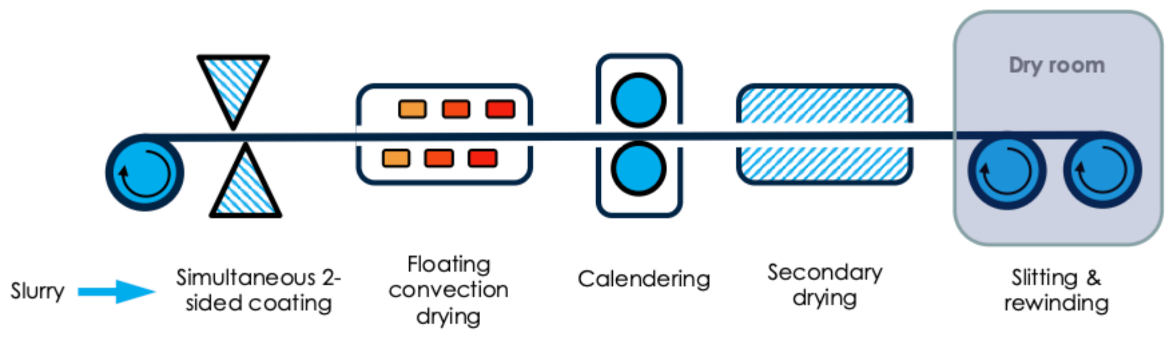

Figure 1. Schematic illustrating production of electrodes using slot-die coating.

1. Physics-based model reduction for real-time control

A two-phase Navier–Stokes/volume-of-fluid model is used as the physics reference:

$$\rho\Big(\frac{\partial \mathbf{v}}{\partial t} + \mathbf{v}\cdot\nabla\mathbf{v}\Big) = -\nabla p + \nabla\cdot\big(\mu[\nabla\mathbf{v} + \nabla\mathbf{v}^\top]\big) - \rho g\mathbf{e}_z + \mathbf{f}_\sigma,$$
$$\nabla\cdot\mathbf{v} = 0.$$

$\mathbf{v}$: velocity, p: pressure, ρ: density, μ: viscosity, $\mathbf{f}_\sigma$: surface tension.

This leads to the **reduced-order-model (ROM)** that separates machine-direction (MD) dynamics from static cross-directional (CD) coupling:

$$h(s) = g(s)\widehat{R}q(s), \qquad g(s) = e^{-\ell s}g_0(s), \qquad g_0(s) \simeq \frac{c_0}{s^2 + c_1 s + c_0},$$

where s is the Laplace variable, $g(s)$ the MD dynamics, ℓ the transport delay, and $\widehat{R} \in \mathbb{R}^{n\times m}$ maps inlet flows $q(s) = (q_1(s), \ldots, q_m(s))^{\mathrm{T}}$ to downstream CD thicknesses $h(s) = (h_1(s), \ldots, h_n(s))^{\mathrm{T}}$. This model is fast enough for feedback while remaining traceable to CFD.

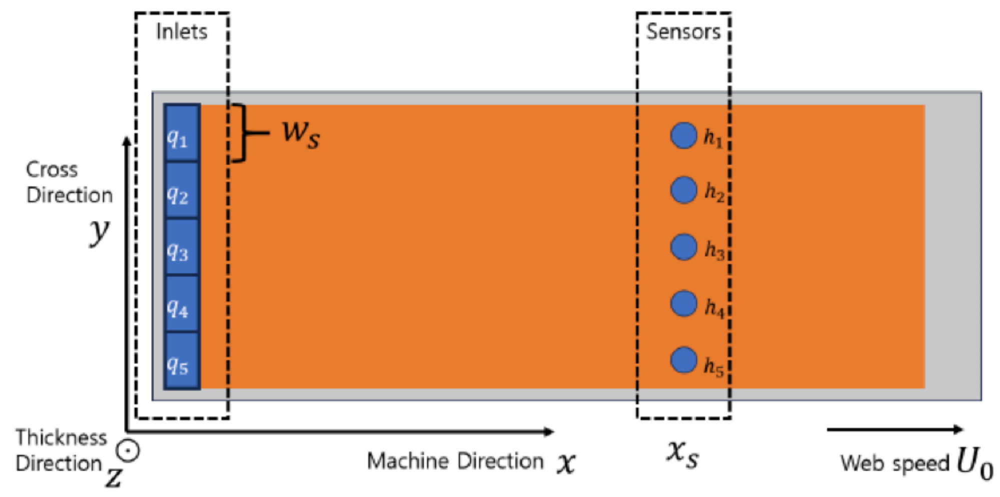

Figure 2. Slot-die configuration: five inlet stripes $q_1, \ldots, q_5$ and five downstream virtual sensors measuring thicknesses $h_1, \ldots, h_5$.

Role of ROM for closed-loop control

The ROM provides a **computationally efficient representation** of the coating process that enables real-time optimisation and feedback control while remaining grounded in high-fidelity CFD. It can be used for:

- **Feedback control:** design controllers that regulate coating thickness in real time.
- **Feedforward optimisation:** determine operating conditions before coating.
- **Process diagnostics:** compare model predictions with measurements to identify disturbances and modelling errors.

The resulting closed-loop architecture is shown below.

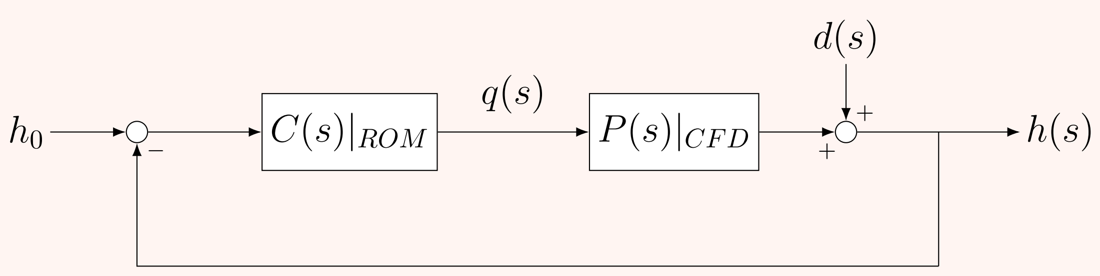

Figure 3. Closed-loop control architecture for slot-die coating with h_0 denoting the target coating thickness, q the inlet flow-rate adjustments, h the measured coating thicknesses, and d disturbances.

Model identification and performance

The PDEs were implemented in OpenFOAM (CFD) to model the slot-die configuration from Fig. 2 with 5 inlets and 5 sensors, and a dataset was generated by applying 10%-magnitude PRBS inlet-flow perturbations. The dataset allowed a ROM to be identified, yielding an RMSE of 3.7–$4.0\,\mu$m ($R^2 \approx 0.98$) across sensors.

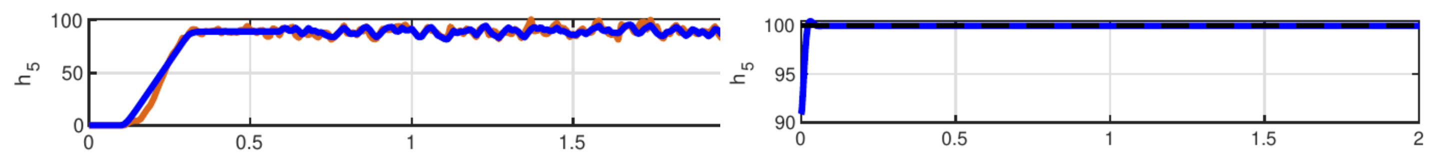

Figure 4. Left: CFD trace (orange) versus ROM output. Right: nominal closed-loop response.

With $K_P = \beta\widehat{R}^{-1}$ and $\beta = 0.1$, the surrogate shows well-damped convergence to $100\,\mu$m with a nearly uniform CD profile. Comparing $\widehat{R}$ with a symmetric PDE-kernel map also reveals edge effects and long-range CD coupling which would be missed by a local model.

2. Sensing Limitations

The coating thickness profile $h(y)$ must be reconstructed from finitely many sensor measurements before it can be used for control. This reconstruction problem is fundamentally limited by the sensing configuration. If these measurements are treated as ideal point samples, unresolved high-frequency profile content can be indistinguishable from the low-order cross-directional modes we want to control. Without stronger assumptions, such as strict bandlimiting, no finite worst-case reconstruction bound is possible.

Aperture-aware recoverability bound

Real sensors average over a finite spot size. By explicitly modelling this aperture, high-frequency alias leakage is attenuated and the low-order Fourier coefficients can be recovered with a certified error bound:

$$\|\widehat{a} - a\|_2 \leq \eta,$$

where a are the low-order Fourier coefficients of the true profile and $\widehat{a}$ their estimates. The bound η captures residual alias leakage and noise amplification, making spot size, sensor count, and robustness margin explicit sensing-design parameters.

From sensing error to control residual

The recoverability bound η propagates through model identification and controller design, ultimately limiting the achievable control accuracy:

$$\text{sensing error} \implies \text{model error} \implies \text{control error}$$

A one-shot inverse update satisfies:

$$\|a^+\|_2 \leq c(\beta)\|a\|_2 + \beta\big(1 + \|R\|_2\delta_{\mathrm{inv}}\big)\eta,$$

where δ_{inv} quantifies the error in the inverse controller caused by identifying an imperfect control model and a^+ are the true coefficients *after* applying the control action. Consequently, the sensing configuration sets a fundamental lower bound on the achievable control performance: no controller can outperform the information provided by the sensing system.

3. Future Work: from CFD to real-world deployment

- **From CD profiles to machine settings.** The controller computes an ideal cross-directional thickness correction, but practical slot-die systems provide only a limited number of adjustable inlet flow zones. An efficient mapping from desired coating profiles to feasible machine settings is therefore required.
- **Accounting for process nonlinearities.** Practical deposition behaviour deviates from the linear control model. Data-driven surrogates or machine-learning methods may complement the physics-based model to compensate for nonlinear effects.
- **Industrial validation.** The proposed framework must be evaluated with industrial partners and on production lines to quantify performance improvements and establish the evidence required for automated closed-loop operation.

The proposed framework supports a transition from trial-and-error manufacturing towards sensor-informed, physics-based, and fully automated electrode coating.

References

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