



Precise control of water and wastewater treatment systems with non-ideal heterogeneous mixing models and high-fidelity sensing

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ABSTRACT

Non-ideal heterogeneous mixing models are developed and incorporated within advanced closed-loop control strategies utilizing high-resolution sensing to maximize the resiliency and minimize the energy consumption of water treatment processes with intelligent model-based decision-making approaches. The proposed non-ideal heterogeneous mixing models capture continuity (heat and mass conservation), yet are extremely simple with few parameters, so they lend themselves to fast online prediction (with extrapolation capabilities) and regular recalibration. Further, they are more accurate than computational fluid dynamics (CFD) (60% less error) and symbolic regression data-driven models (73% less error). Real-time high-resolution sensor data are collected for observing spatiotemporal responses of state variables (conductivity, pH, and temperature) to transient influent shocks. Deterministic global dynamic optimization is used for training and recalibration of the non-ideal heterogeneous mixing models to guarantee the best-possible fits to the sensor data. The models are then deployed within standard model-predictive control and two economic model-predictive control strategies to demonstrate model-based decision-making for disturbance rejection and optimal operation of aeration in a continuous flow nitrification system utilizing high-resolution sensor data from several spatial positions. The new technology platform, consisting of high-resolution sensors, non-ideal heterogeneous mixing modeling, deterministic global dynamic optimization, and model-predictive control, offers superior performance over current approaches in water and wastewater treatment processes.

1. Introduction

The urgent demand for enhanced water quality, high resilience, high treatment efficiency, low costs, and environmentally-friendly operations have promoted the development of model-based decision-making and control strategies in water and wastewater treatment plants (WTPs and WWTPs) [1–4]. The prerequisite to an effective control system is the ability to measure important water quality information (e.g., conductivity, pH, temperature, etc.) by high-fidelity sensing technologies, that can then be used to build reliable predictive models as well as for real-time state measurement. Though classical, purely physics-based unit operations models (e.g., activated sludge model (ASM) [5–8], a hydraulic model [9], and a sedimentation tank model [1,10]) have been used extensively in the past, they have their limitations. For example,

building models is time-consuming and some necessary parameters (e.g., cell growth rate, biomass yield) in these models are unmeasurable in WTP/WWTPs in real-time. Such variables are normally determined by offline analyses in the laboratory, causing serious time delays [1,11,12] in operator response. As a consequence, transients and spatial heterogeneity in process units go undetected, hampering efficiency improvement efforts due to an incomplete understanding of the transport processes of water quality information [13–15].

In situ data-driven approaches could overcome the existing modeling drawbacks by enabling the identification of the “black box” systems (e.g., aeration tanks) using data from the practical process under real operating conditions [16,17]. However, traditional data-driven methods in WTPs/WWTPs have two obstacles. First, some data-driven models are developed based on markedly large data acquisition and processing over

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long periods. Unfortunately, in many situations only a small amount of data points have a critical influence on the system. Thus, using excess data will dilute important signals, and is unsuitable for identifying transient situations (e.g., fast chemical transport processes) [13]. The second limitation is that pure data-driven approaches are based on regression without considering physical principles, even for less complicated phenomena (e.g., dynamic neural network prediction of flow rate [18]) in WTP/WWTPs, and are therefore limited to interpolated prediction. These data-driven identification techniques may perform well for complicated systems since empirical correlations and first-principles may not accurately capture the behavior of the system due to limited information [18,19]. As a result, these models are unable to capture important fundamental mechanisms, and thus are generally less functional for further model-based control applications where extrapolative prediction is needed. Fortunately, well-understood phenomena, like heat and mass transport, can be readily and accurately modeled using first-principles.

This study explores an innovative approach to obtain high-resolution spatiotemporal data from real-time *in-situ* water quality sensors, build and validate accurate models for the measured water quality parameters, and deploy those models for precise model-based control of WTP/WWTPs. Simple non-ideal heterogeneous mixing models are developed to simulate and predict heterogeneous mass transport in WTP/WWTPs. In order to achieve visualization of the whole system, the transport characteristics of three important attributes of water quality (conductivity [20], pH [21], and temperature [22]) are elucidated with only a small volume of data collected within short periods (e.g., 2–10 min). These models are then utilized within a technology platform for the precise control of WTP/WWTPs using several different control strategies and architectures, including conventional and economic model-predictive control for improving energy and chemical-use efficiency in WTP/WWTPs.

One novel contribution of this study is that deterministic global (dynamic) optimization [23–27] is employed for better understanding the heterogeneous mixing phenomena via rigorous parameter estimation. Finding a global optimum is far more difficult than finding an arbitrary local solution; yet, a mismatch between the model and the data cannot be declared unless the best-possible fit is verified. Therefore, this approach provides additional benefits for preventing erroneously invalidating proposed mechanisms in cases where local algorithms return poor, suboptimal fits. A comparison between local and global optimal

solutions within this context is shown in Fig. 1, illustrating the conductivity profile in different positions of a tank. As shown, the sub-optimal solution obtained by a local optimization algorithm [28,29] differs significantly from a global solution. The advantages of the developed non-ideal heterogeneous mixing models are demonstrated through their straightforward, interpretable mathematical expressions able to achieve a better fit as compared to both pure data-driven symbolic regression machine learning approaches using Eureqa® (Version 1.24.0 (build 9367), DataRobot) [66] and a pure computational fluid dynamics (CFD) approach. Furthermore, the predictive capabilities are also validated by additional experimental datasets of chemical species (e.g., KCl, MgSO₄, NaOH), verifying that provided models could work for model-predictive control (MPC) in a broad spectrum of operating scenarios.

This paper is organized as follows. In Section 2, the Materials and Methods used in this study are presented. Summarily, the experimental methods are discussed as well as the model development, rigorous parameter estimation, and the control architectures for precise control of WWTPs. Section 3 contains the Results and Discussion, whereby the performance of the non-ideal heterogeneous mixing models is demonstrated, as are the control architectures for precise control of WWTPs. Conclusions follow in Section 4.

2. Materials and methods

Fig. 2 illustrates at a high level, the methods used in this study. In Fig. 2a, we illustrate the experimental methods for data acquisition as discussed in Section 2.1. Fig. 2b illustrates the overall schematics of calibration (detailed in Section 2.3) and advanced control strategies of WTP/WWTPs developed in this work (detailed in Section 2.4). Fig. 2c illustrates a continuous flow nitrification reactor representative of a commercial WWTP operation (detailed in Section 2.4).

2.1. Non-ideal mixing profiling using Milli-Electrode array (MEA) sensors

All three types of MEA sensors (each size: 2 cm × 0.5 cm) targeting three water quality parameters (conductivity, pH, and temperature) were precisely printed on Kapton polyimide film (FPC, thickness: 127 μ m, American DuraFilm) by a Dimatix Materials Printer (ModelDMP-2800, FUJIFILM Dimatix, Inc.) as previously reported [30,31]. Three assemblies of MEA sensors of each were deployed at three locations (high position: 40 mm below the water surface; middle position: 85 mm below the water surface; low position: 130 mm below the water surface) of a batch stirred reactor (diameter: 62 mm, height: 180 mm) (Fig. 2a) to accurately profile the whole reactor.

The sensor readings were recorded by a multi-channel potentiostat (1040C 8-channel potentiostat, CH Instruments, Inc.) every 2 s. It took 10 min to reach steady-state operation with continuous stirring with a rotation rate of 50 RPM. Then, different species (chemicals purchased from Fisher Science, Co.) were individually injected into the reactor to simulate transient shocks. Specifically, for conductivity shocks, 200 μ L (100 g/L) sodium chloride was injected into the reactor on the three locations (high, middle, and low) respectively. For pH shock, 200 μ L (1 M) potassium hydroxide solution mixed in 2 mg/L sodium chloride solution (pH = 14) was injected into the reactor (initial pH: 7.22) on the three locations (high, middle, and low) in turn. For temperature shock, the water solution in the reactor (initial temperature: 18.5 ± 0.12 °C, room temperature) was placed on a heating plate that was heated to 200 °C within 30 s and then shut off. All shock tests were conducted with three repeated experiments and the average values were calculated to compensate for the uncertainty in experimental procedure. Validation tests were carried out under the same conditions, except the shock substance was changed to 200 μ L KCl solution (100 g/L) and 200 μ L MgSO₄ solution (100 g/L) for conductivity model validation, and to 200 μ L NaOH solution (1 M) for pH shock validation. These shock substances were only injected into the high zone of the reactor.

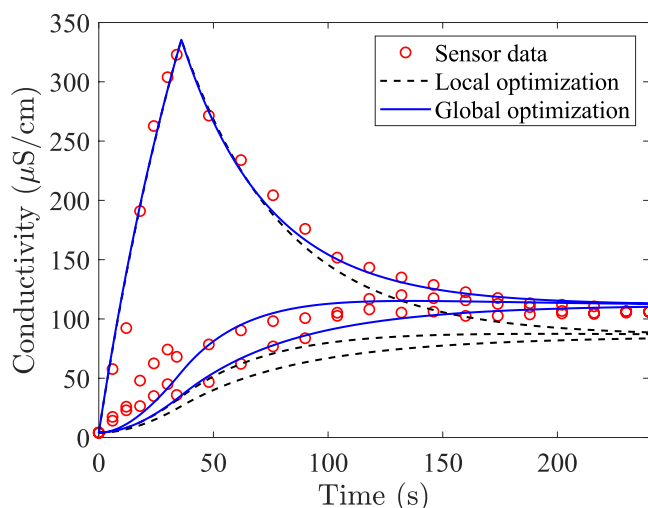


Fig. 1. Comparison of the conductivity profiles using local optimization (black dashed lines) and global optimization (blue solid lines) are presented in this figure. The conductivity model is a dynamic system under a pulse response. The three trajectories represent profiles in three different positions of the tank (high, middle, and low zones).

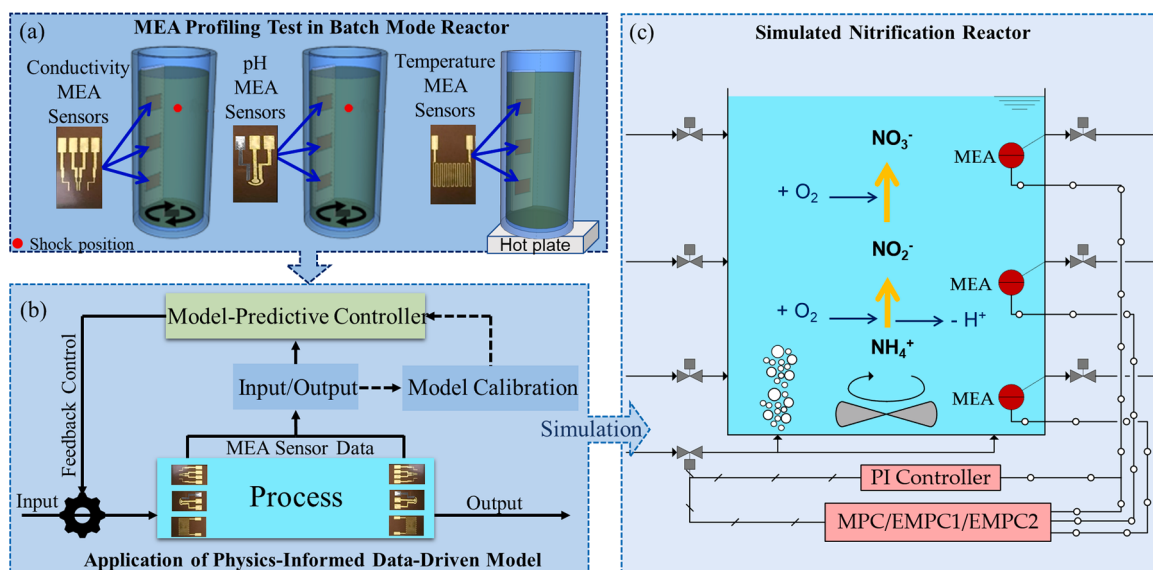


Fig. 2. (a) The experimental setup is illustrated for profiling tests along the batch reactor depth under the conductivity shock, pH shock, and temperature shock measured by the MEA sensors. (b) A schematic of the application of non-ideal heterogeneous mixing models in an online model-predictive controller (MPC) system is illustrated. (c) The simulated continuous stirred tank nitrification reactor is illustrated with inflows and outflows located at high, middle, and low zones, and a PI controller or MPC for controlling aeration.

2.2. Non-ideal mixing model development

Non-ideal heterogeneous mixing models were developed to simulate conductivity, pH, and heat transport processes inside the reactor. Specifically, to capture the spatiotemporal heterogeneity of the conductivity and pH profiles, the tank reactor was modeled using multiple regions with interchange [32]. The models were established based on heat and mass conservation that characterize the observed physical phenomena. These models were then used within a continuous flow nitrification

reactor model for precise control.

2.2.1. Conductivity mixing model

In this section, non-ideal mixing models are developed to capture the conductivity heterogeneity with respect to sensor measurements at different positions. The tank was partitioned into different nominal zones based on the positions of three MEA conductivity sensors (Fig. 3a–3c). The high, middle, and low zones represent the regions corresponding with the sensor assigned within that location. The mixing zone

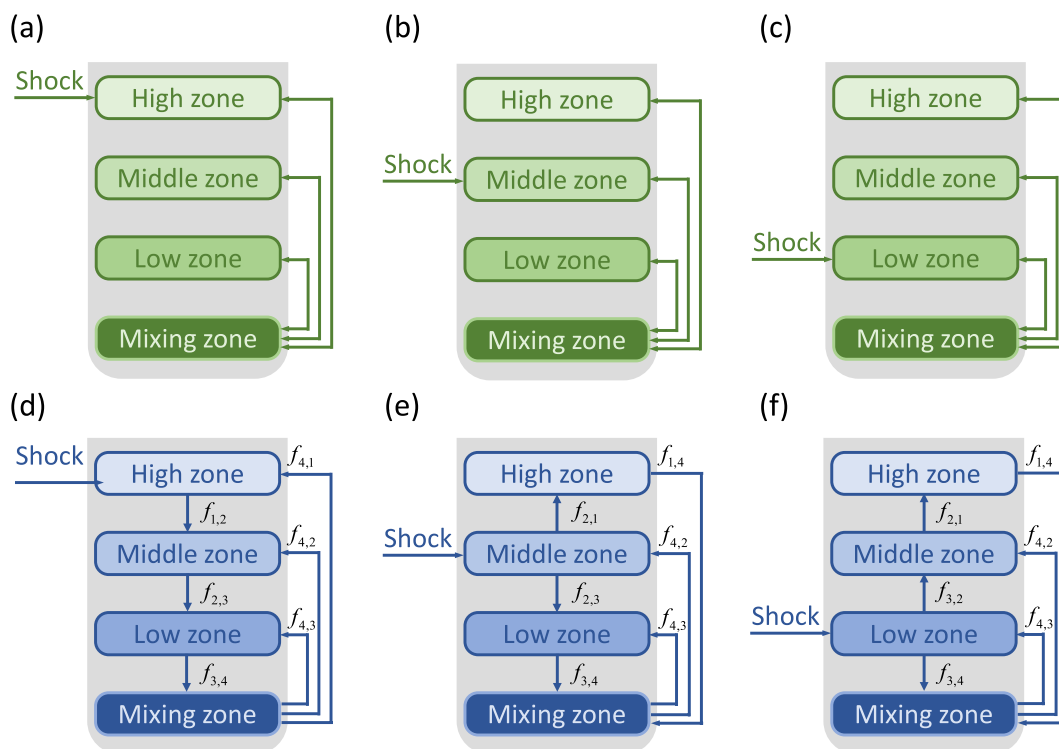


Fig. 3. Schematics of the NaCl electrolyte conductivity transport model are illustrated for shocks injected at (a) high zone, (b) middle zone, and (c) low zone, and the hydroxide ion transport model with shocks injected at (d) high zone, (e) middle zone, and (f) low zone.

represents the region where the stirrer resides on the bottom of the reactor. The dominant mechanism for mixing is forced convection, which is significantly greater than the diffusive mixing between each zone [33]. Thus, it was assumed that the stirring power dominates the mass transfer in the reactor under fast stirring, while the diffusion between adjacent zones could be neglected. The Reynolds number for the conductivity experiments is $Re = 1198.76$ (calculation process is introduced in Section 3.1), which coincides with the laminar/turbulent transition region in an agitated cylindrical tank. The ion transport between the mixing zone and each sensor zone is defined as:

$$\begin{aligned} \frac{dC_i}{dt} &= \frac{1}{4V}k_i(C_0 + C_4 - C_i), \quad i = 1, 2, 3, \\ \frac{dC_4}{dt} &= \frac{1}{4V}k_4(C_1 + C_2 + C_3 - 3C_4) \end{aligned} \quad (1)$$

Here, C_i represents the electrolytic conductivity ($\mu S/cm$) of the solutions in each zone ($i = 1, 2, 3, 4$), V is the volume of the reactor (0.38 L), and k_i is a volumetric mass transfer coefficient (L/s) that represents the rate of forced convective mass transfer between the mixing zone and zone i . C_0 represents the inlet conductivity in the corresponding zone, which is equal to C_v (shock conductivity, $\mu S/cm$) in the zone with the injected shock during the injection period (i.e., the time duration for which the conductivity in the injection zone rises to a peak) or zero for other cases (note: nomenclature of all mathematical symbols, subscripts, and superscripts appearing in equations are listed in Table S1 of the supplementary information (SI)). Three series of experiments were performed, where a high-concentration shock solution was injected into each high, middle, and low zones. The corresponding model was then developed based on the injection position.

2.2.2. pH mixing model

In this section, non-ideal mixing models are established to capture pH heterogeneity within the high, middle, and low zones of the reactor. As the solute, hydroxide ions exhibit anomalously high apparent mobilities in aqueous solutions [34,35]. Previous studies found that this anomalous transport behavior at the molecular level [36] was attributed to continuous interconversion between a hydration complex of hydroxide ions and water molecules. Thereby, apart from forced convection and diffusive transport, the hydroxide ions undergo electrochemical interactions with water molecules, grabbing protons from adjacent water molecules to generate hydroxide ion clusters at adjacent new sites. The superficial transfer coefficients are introduced to represent these multifactorial interactions between each zone (Fig. 3d-3f). Three independent experiments were conducted with shocks injected at high, middle, and low injection positions. Different models are developed based on the corresponding transfer mechanism, as illustrated in Fig. 3d-3f. For the KOH shock high-zone injection case, the model is established as:

$$\begin{aligned} \frac{dH_1}{dt} &= \frac{1}{v_1 V} (H_0 + \kappa_1 H_4 - \kappa_1 H_1), \\ \frac{dH_2}{dt} &= \frac{1}{v_2 V} (\kappa_1 H_1 + \kappa_2 H_4 - (\kappa_1 + \kappa_2) H_2), \\ \frac{dH_3}{dt} &= \frac{1}{v_3 V} ((\kappa_1 + \kappa_2) H_2 + \kappa_3 H_4 - (\kappa_1 + \kappa_2 + \kappa_3) H_3), \\ \frac{dH_4}{dt} &= \frac{1}{(1 - v_1 - v_2 - v_3)V} ((\kappa_1 + \kappa_2 + \kappa_3) H_3 - (\kappa_1 + \kappa_2 + \kappa_3) H_4) \end{aligned}$$

In this model, H_i represents the pH corresponding to each zone ($i = 1, 2, 3, 4$) in the reactor, v_i is the volume fraction of zone i , and κ_i is the superficial transport coefficient, indicating the “flow rate” of OH^- between adjacent zones that accounts for both reaction and convection transport (L/s). H_0 represents the input in the high zone which is equal to H_v (shock pH) during the injection period (0–8 s) and is equal to zero for the remaining process. The details and the development of pH

models for middle and low zone injection cases are summarized in Section S1 of the SI.

2.2.3. Temperature profiling model

Heat transport was assumed to be significantly slower than fluid transport [33], indicating that the transport process of heat in each sensor zone should be the same (as shown in Fig S1 of the SI). Thus, only a single equation is required to accurately model the bulk fluid temperature based on the energy balance for the batch system [37]:

$$\frac{dT}{dt} = -\frac{UA_c}{V\rho C_p}(T - T_c).$$

Here, T is the temperature of the water solution ($^{\circ}C$) and A_c is the cross-sectional area of the cylindrical container (m^2) across which heat transfer is occurring. ρ and C_p are respectively the density (kg/m^3) and heat capacity ($kJ/(kg \cdot ^{\circ}C)$) of the water ($\rho = 998.19$, $C_p = 4.18$). T_c is the temperature of the inner face of the bottom of the reactor and U is the overall heat transfer coefficient of the system ($kW/(m^2 \cdot ^{\circ}C)$). The full details for the development of the temperature model are presented in Section S2 in the SI.

2.3. Parameter estimation and model validation using global dynamic optimization

Rigorous deterministic global optimization was used to determine the uncertain parameters for validation of optimal mixing models to capture the mixing dynamics for the three targeted properties (e.g., conductivity, pH, and temperature). The general form of the global dynamic optimization problem is defined as:

$$\begin{aligned} \min_{\mathbf{p} \in \Pi \subset \mathbb{R}^{n_p}} \quad & \phi(\mathbf{x}(\mathbf{p}, t_1), \dots, \mathbf{x}(\mathbf{p}, t_{N_t}), \mathbf{p}) \\ \text{s.t.} \quad & \dot{\mathbf{x}}(\mathbf{p}, t) = \mathbf{f}(\mathbf{x}(\mathbf{p}, t), \mathbf{p}, t), \quad \forall t \in I = [t_0, t_f] \\ & \mathbf{x}(\mathbf{p}, t_0) = \mathbf{x}_0(\mathbf{p}). \end{aligned} \quad (2)$$

In this formulation, ϕ is the objective function formulated as the sum of squared error (SSE) between the model and the experimental data at specific discrete time points $t_1, \dots, t_{N_t}$, corresponding with the experimental data, for each zone in the tank. $\mathbf{x}$ is the generic state variable vector which represents $\mathbf{C} = (C_1, C_2, C_3, C_4)$ for the conductivity model, $\mathbf{H} = (H_1, H_2, H_3, H_4)$ for the pH model (H_1, H_2, H_3 , and H_4 represent the pH value in the corresponding zones), and T for the heat transfer model. $\mathbf{p}$ is the uncertain parameter vector requiring estimation by optimization, which belongs to the parameter set $\Pi \subset \mathbb{R}^{n_p}$. $\mathbf{x}_0$ is the initial condition vector for $\mathbf{x}$ at $t = t_0$. The optimization problem is nonconvex and constrained by a system of ordinary differential equation (ODE) initial value problems (IVPs). The specific optimization formulations for conductivity and pH mixing models are summarized in Section S3 of the SI.

There has been active development of novel deterministic methods for solving eq(2) to guaranteed global optimality [25,38–41]. In this study, for conductivity and pH models, the nonlinearity comes from the bilinear terms of the system of ODEs. To solve the parameter estimation problems for these models, the models were reformulated into a system of nonlinear algebraic equations using an explicit Euler discretization and accounted for as equality constraints. As a result, the bilinear terms become recursively multiplied, resulting in the feasible set being nonconvex. The ANTIGONE v1.0 solver [42] in GAMS v24.7.4 [43] was used to solve these parameter estimation problems to guarantee global optimality (absolute stopping tolerance is set to 0; relative stopping tolerance is set to 0.1; absolute feasibility tolerance is set to 1E-6). All global optimization results were obtained within 1.5 h, which is important for applications in real-time MPC of WTPs/WWTPs with a much longer residence time. The analytical expression for the temperature model was derived and applied within the global optimization formulation (Section S4 in the SI). The global optimization problem for the temperature model was solved using the EAGO v0.2.1 solver (EAGO).

jl) [65] in the Julia programming language [44] via the JuMP v0.18 modeling language (JuMP.jl) [45]. The global results for the temperature model could be obtained within 2 min, which is appropriate for prompt temperature control in WTPs/WWTPs. The wall clock times were reported for GAMS and JuMP implementations run on a personal workstation with an Intel Xeon E3-1270v5 4-core/8-thread processor at 3.60 GHz/4.00 GHz (base/turbo) frequency running Windows 10 with 32 GB of ECC memory.

2.4. Precise control of a wastewater nitrification system

The non-ideal heterogeneous mixing models for conductivity were expanded from a batch system to an unsteady pilot-scale continuous flow nitrification CSTR (1000L) to demonstrate their applicability to real WWTPs, with a controller being implemented to showcase disturbance rejection and energy saving operations (Fig. 2c). Three inlet streams continuously flow into the tank corresponding to the high, middle, and low zones. Similarly, three outlet streams continuously flow out of the tank at the corresponding zones. In addition, there is an air diffuser at the tank bottom continuously aerating for nitrification to oxidize NH_4Cl [46]. A conductivity sensor is deployed in each zone to measure the corresponding conductivity at 10 s intervals. An impeller is in the mixing zone to continuously stir the liquid inside the tank. For traditional proportional-integral (PI) control, feedback is provided from the high-zone MEA conductivity sensor and a control signal is sent to the valve on the air stream at the bottom of the vessel. For MPC and its variants, sensors in each zone are utilized for feedback.

A modified conductivity mixing model that accounts for continuous operations in this tank is established to simulate the nitrification step:

$$\begin{aligned}\frac{dC_i}{dt} &= \frac{1}{4V} (k_i(C_4 - C_i) + \dot{m}_{in,i}C_{in,i} - \dot{m}_{out,i}C_i) + R_{\text{NH}_4^+}, \quad i = 1, 2, 3, \\ \frac{dC_4}{dt} &= \frac{1}{4V} k_4(C_1 + C_2 + C_3 - 3C_4) + R_{\text{NH}_4^+}, \\ \frac{dc_O}{dt} &= r_O + k_{la}(c_O^* - c_O),\end{aligned}\quad (3)$$

where $\dot{m}_{in,i}$ and $\dot{m}_{out,i}$ are continuous inlet and outlet flow rate at zone i (L/s), respectively, $C_{in,i}$ represents the conductivity of the inlet stream at zone i ($\mu\text{S}/\text{cm}$), and $R_{\text{NH}_4^+}$ is the reaction rate law for NH_4^+ consumption measured as conductivity ($\mu\text{S}/\text{cm}/\text{s}$), c_O is the oxygen concentration (mg/L), and r_O is the oxygen consumption rate described by a reaction rate law (mg/L/s). The aeration process is modeled by the rate of mass transfer of oxygen into the reactor liquid from air bubbles $k_{la}(c_O^* - c_O)$, where k_{la} is the volumetric mass transfer coefficient (s^{-1}) [47], and c_O^* is the saturated dissolved oxygen concentration (9.1 mg/L at 20 °C) [48]. The standard oxygen transfer rate (SOTR, mg/s) is defined as $\text{SOTR} = k_{la}c_O^*V$, and represents the amount of oxygen transferred per second at 20 °C. The standard oxygen transfer efficiency (SOTE, %) refers to the ratio of oxygen in the inlet air stream dissolved in the liquid at 20 °C, given by $\text{SOTE} = \text{SOTR}/W_O$, with W_O the mass flow of oxygen in the air stream (mg/s). W_O can be calculated by an empirical formula: $W_O = 0.2967Q$, where Q is the airflow rate adjusted by the controller. The mass transfer coefficients were adjusted to construct a modified model that can account for all situations with single or multiple shocks at high,

middle, and low zones. The model development process, the detailed kinetics for the nitrification reaction, and the mechanism for airflow and transfer into the liquid are introduced in Section S4 in the SI.

A case study of removing excess NH_4Cl in a nitrification CSTR of a WWTP is simulated as shown in Fig. 2c. The input and output variables for the control system are given in Table 1. According to the standard of moderate municipal wastewater, the concentration of ammonium ions in the effluent should not exceed 30 mg $\text{N-NH}_4^+/\text{L}$ [49]. Thus, the operating setpoint (SP) is set at 280 $\mu\text{S}/\text{cm}$ corresponding to the standard concentration. Independent numerical experiments were conducted to assess the behavior of the system under four different influent shock conditions (i-iv) and six different operating scenarios to compare the system performance with various control approaches. From $t = 2100$ s to $t = 2250$ s, influent shocks (as step disturbances) in NH_4Cl concentration were introduced in each case as: (i) $C_{in,1} = 320\mu\text{S}/\text{cm}$, (ii) $C_{in,2} = 320\mu\text{S}/\text{cm}$, (iii) $C_{in,3} = 320\mu\text{S}/\text{cm}$, (iv) $C_{in,1} = 300\mu\text{S}/\text{cm}$, $C_{in,2} = 350\mu\text{S}/\text{cm}$ and $C_{in,3} = 270\mu\text{S}/\text{cm}$.

2.4.1. Proportional-Integral (PI) control

A traditional closed-loop PI-controller was modeled and tuned for rejecting influent conductivity shocks. The PI controller only makes decisions based on feedback signals from measurements in the high zone and adjusts the mass flow rate of air entering the system. The Internal Model Control (IMC) correlations are used to tune the PI parameters at first. Then, the parameters are further adjusted manually through simulations until the closed-loop system performs as desired. The details of the PI tuning process are introduced in S3 of the SI. An experiment is performed on the system with a unit step disturbance to evaluate the control performance, the integral time-weighted absolute error (ITAE), integral time-weighted squared error (ITSE), integral absolute error (IAE) and integral squared error (ISE) are quantified with a settling time set as 1000 s, as listed in Table 2. The economic performance of the PI controller was assessed based on energy consumption and concentration disturbance rejection under the four influent shock scenarios.

2.4.2. Model predictive control (MPC)

MPC is an advanced control technique widely used in the process industries. MPC has been proposed for applications in WTPs/WWTPs to deal with the complexities from disturbances in the influent and physical and chemical phenomena [50–52]. MPC allows for tunable closed-loop response with its primary advantage being its intuition of process dynamics and capability to naturally handle multi-input/multi-output systems. In addition, compared with conventional proportional-integral-derivative (PID) control and interval model control (IMC), MPC can handle more complicated systems (e.g., time delay, nonlinearity, open-loop instability), and provide a better response with less settling time. Therefore, a multi-input MPC was designed to improve disturbance (step function) rejection in WTP/WWTPs. The core concept of MPC is to solve an optimization problem at predetermined time points k to determine a control action that best drives the system towards the SP. In this study, the control action step size δ is set as 10 s (i.e., same as for PI control). An objective function is formulated as the sum of squares of the predicted errors (differences between the SP and the model-predicted outputs) over a prediction horizon of P control action steps [53]:

$$\min_{u_k, \dots, u_{k+M-1}} \sum_{i=1}^3 \sum_{j=1}^P \left(\text{SP} - \hat{C}_{i,k+j} \right)^2. \quad (4)$$

Table 1

Input and output variables for the nitrification wastewater system with different control strategies are listed in this table.

Control system	PI control	MPC, EMPC1, EMPC2
Input variables	Q Airflow rate	Q Airflow rate
Output variables	C_1 High zone conductivity	C_1 High zone conductivity
		C_2 Middle zone conductivity
		C_3 Low zone conductivity

Table 2

The control performance indices quantified by a response to a step disturbance change are presented in this table. The settling time is set as 1000 s.

Performance index	ITAE	ITSE	IAE	ISE
	2.817E4	1.606E3	5.414E1	3.185

Here, u_m ($m = k, \dots, k + M - 1$) is the control variable which is equal to the airflow rate Q in this study (kg/s), SP is the setpoint ($\mu\text{S/cm}$), $\hat{C}_i$ is the model predicted output ($\mu\text{S/cm}$) in zone i , and the subscripts indicate the sample time (k is the current sample time). P is the number of control actions in the prediction horizon ($P = 20$), and M is the number of control actions in the control horizon ($M = 3$). M control variables $u_k, \dots, u_{k+M-1}$ are optimized at control action step k , but only the first control action u_k is implemented. Then, similarly, a new optimization problem is solved with respect to M control variables over a prediction horizon of P at step $k + 1$. The dynamic matrix control (DMC) method was used to evaluate model predicted process outputs $\hat{C}_i$ [53]. The performance of the MPC was assessed based on energy consumption and concentration disturbance rejection under the four influent shock scenarios.

2.4.3. Economic model predictive control (EMPC)

Economic MPC (EMPC) is a method for accounting for real-time

process operations with respect to economic performance [54]. As such, EMPC can directly account for process economics in the determination of appropriate control response, and therefore is ideal for the development of next-generation WTP/WWTPs, such as real-time energy management and market-driven production [55,56]. In this study, we formulate and implement EMPC with two different objectives: one is targeted at reducing environmental discharge (EMPC1); and the other is targeted at saving energy (EMPC2). The optimization problem for EMPC1 is defined as

$$\min_{u_k, \dots, u_{k+M-1}} \sum_{i=1}^3 \sum_{j=1}^P D_{i,k+j}^2 + w \left(\sum_{i=0}^{M-1} u_{k+i} + (P - M + 1) u_{k+M-1} \right), \quad (5)$$

where D_i is the discharge from zone i ($\mu\text{S/cm}$), that can be expressed as

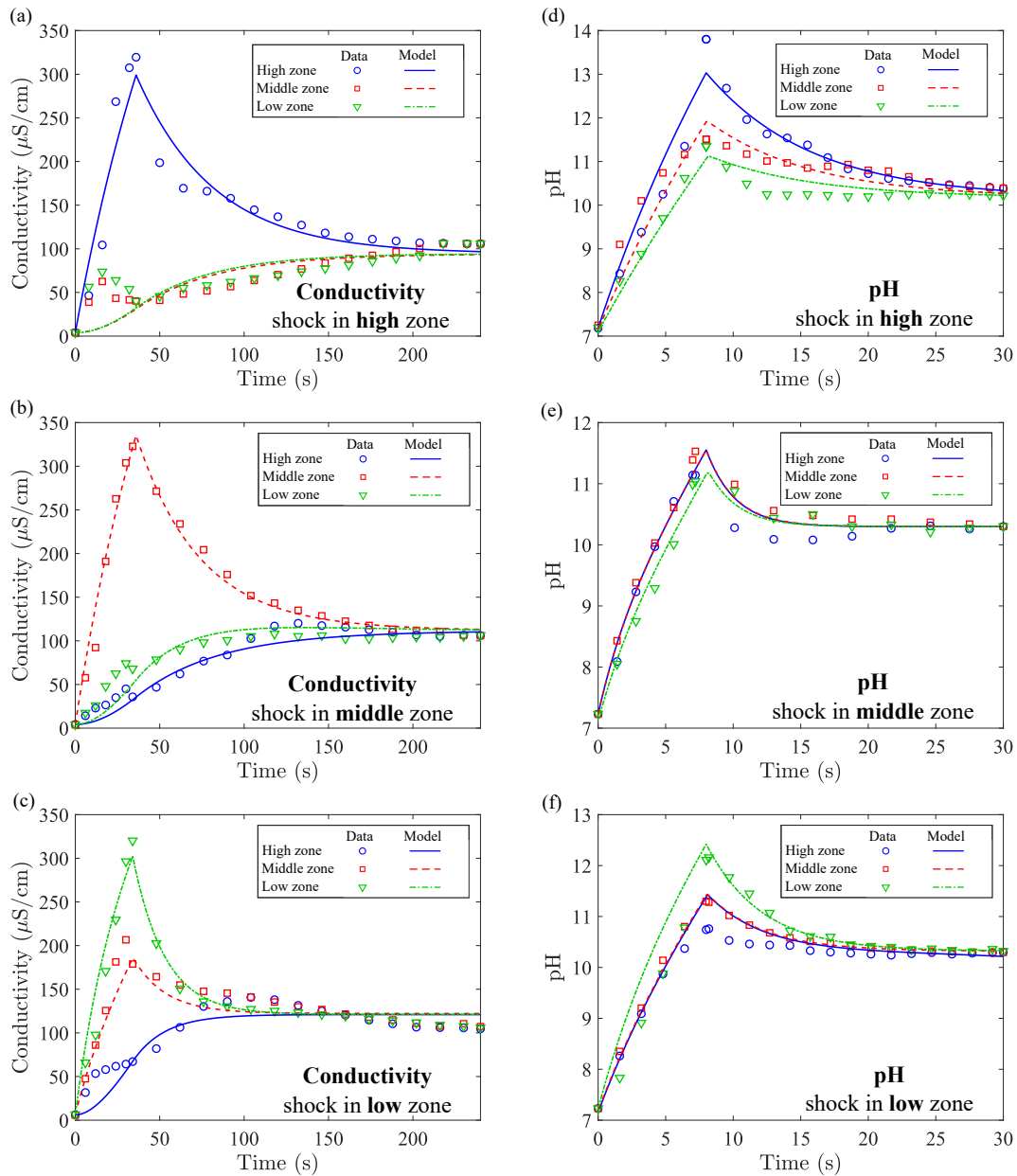


Fig. 4. Optimal conductivity profiles from the global optimization results are plotted against a subset of data for (a) the high-zone injection model, (b) middle-zone injection model, and (c) low-zone injection model. Optimal pH profiles from the global optimization results are plotted against a subset of data for (d) the high-zone injection model, (e) middle-zone injection model, and (f) low-zone injection model.

$$D_{i,k+j} = \begin{cases} \hat{C}_{i,k+j} - SP & \text{if } (\hat{C}_{i,k+j} - r) > 0 \\ 0 & \text{if } (\hat{C}_{i,k+j} - r) \leq 0. \end{cases}$$

The objective is to minimize the overall discharge above the SP over the prediction horizon of P . $w \left(\sum_{i=1}^{M-1} u_{k+i} + (P-M+1)u_{k+M-1} \right)$ in eq(5) is a penalty function with respect to the control variables that guarantees the lowest oxygen consumption when the discharge is already below the SP (the penalty coefficient w is set as 0.03) and penalizes oxygen consumption when making control decisions.

EMPC2 is formulated as the constrained optimization problem:

$$\begin{aligned} \min_{u_k, \dots, u_{k+M-1}} & \delta \left(\sum_{i=0}^{M-1} u_{k+i} + (P-M+1)u_{k+M-1} \right) \\ \text{s.t. } & \hat{C}_{i,k+j} - SP \leq 0, \quad \forall i = 1, 2, 3, \quad j = 1, \dots, M, P. \end{aligned} \quad (6)$$

We seek to minimize the overall oxygen consumption over the prediction horizon to reflect energy management during operations. The inequality constraints ensure that the conductivity profiles over the control horizon, and at the end of the prediction horizon, will be at or below the SP. The performance of each EMPC was assessed based on energy consumption and concentration disturbance rejection under the four influent shock scenarios.

3. Results and Discussion

3.1. Optimal solutions for Conductivity, pH, and temperature mixing models from parameter estimation

The global optimal solutions for parameters of conductivity and pH models are listed in Table S2 in the SI. The time costs for solving these global optimization problems are reported in Table S3 in the SI. The vast disparity in solution times for solving pH problems is due to the “curse of dimensionality” of deterministic global optimization [57] as the high-zone injection problem has nearly double the optimization variables of the low- and middle-zone injection problems.

The optimal conductivity profiles for different injection positions are presented in Fig. 4a-4c. Overall, the conductivity profiles fit the experimental data well, and are able to capture the transient peaks caused by shock injections. This detection of transient maximum conductivity is of great importance in applications such as preventing the damage to bacterial cells in WWTPs [58], since both nitrogen removal and phosphorus removal processes in WWTPs exhibit significant changes in the conductivity of wastewater [59]. For the high-zone injection case (Fig. 4a), it is observed that the optimal profiles in the middle and low zones do not exhibit small peaks like the data, indicating that the lower zones of the physical system receive ionic solutes from the upper zones in small amounts, which is not accounted for in the proposed model. Since the relative mismatch is quite small, no change was deemed necessary for the model. The low-zone injection profile (Fig. 4c) exhibits two conductivity peaks in the low zone and middle zone, which may be attributed to the shock injection position (low zone) being very close to the mixing zone, thus transport to the middle zone occurs rapidly. In addition, the optimal parameter C_v^* for the low-zone injection case is much smaller than the high-zone and middle-zone cases (Table S2 in the SI), indicating that the mixing force quickly dilutes the shock in the low zone due to the closest proximity to the mixing zone.

The optimal pH profiles are shown in Fig. 4d-4f. The models fit well for high-zone and middle-zone injections, while a small deviation can be observed in the high-zone pH profile in the low-zone injection model. The pH profiles for the middle-zone injection are more uniform, due to the equal probability for apparent OH^- transport towards the high and low sensor zones, supporting the hypothesis that the dominant driving force for apparent OH^- transport is the electrochemical reaction instead

of forced convection. As compared with the conductivity transport model, proton (charge) transfers much faster (~ 30 s to achieve equilibrium).

The optimal parameter values for the temperature model are $U^* = 1.9183$ and $T_c^* = 26.40$. It took 65.97 s to solve the parameter estimation problem to global optimality. Since the entire system was considered as a single stirred batch reactor (conforming to the well-mixed assumption), the optimal profile exhibits no spatial variations between each sensor zone and fits the data (Figure S1 in the SI) almost exactly. Furthermore, the convective heat transfer coefficient was also estimated, using fundamental heat transfer principles and the Nusselt number (Nu), which is the ratio of convective to conductive heat transfer across a boundary. The Nusselt number is defined as $\text{Nu} = h_l D_c / \lambda$ [33], where h_l is the convection heat transfer coefficient of the flow equivalent to the overall heat transfer coefficient U for this heat transfer model, λ is the thermal conductivity of water ($\text{W}/(\text{m} \cdot ^\circ\text{C})$) listed in Table S8 in the SI, and D_c is the characteristic length that is equal to the surface area A_c divided by the perimeter P_c of the bottom inner surface ($D_c = A_c / P_c = 0.01375$). In general, the Nusselt number can be calculated as a function of the Reynolds number (Re) and the Prandtl number (Pr). In this experiment, a cubic stirring bar ($d = 38$ mm) was used at a rotation speed (ω) of 50 RPM ($5/6 \text{ s}^{-1}$). The Reynolds number is then calculated as $\text{Re} = \rho d^2 \omega / \mu = 1198.76$, indicating that it is within the transitional region for flow in a cylindrical tank ($1000 < \text{Re} < 10000$), where μ is the viscosity of water ($\text{Pa} \cdot \text{s}$) listed in Table S8 in the SI. The Nusselt number (Nu) for this system can then be calculated by $\text{Nu} = 0.664 \text{Re}^{0.5} \text{Pr}^{1/3} = 44.405$ [60], where Pr is the Prandtl number of water listed in Table S8 in the SI. Finally, the heat transfer coefficient can be estimated as $h_l = \lambda \text{Nu} / D_c = 1.9289 \text{ kW}/(\text{m}^2 \cdot ^\circ\text{C})$, which is very close (0.55% deviation) to the optimal solution U^* . Additionally, the optimal surface temperature T_c^* was higher than the observed solution temperature, which is consistent with the observed heat transfer (raising solution temperature) over the entire time horizon. The observed temperature profile shows a significant reduction in heat transfer rate as the solution temperature approaches T_c^* as the rate of temperature increase (i.e., heat transfer) slows down over this period.

3.2. Comparison of Non-ideal mixing models with pure Data-Driven models and CFD models

CFD models account for complex physical phenomena [61] and therefore are extremely computationally expensive. Typical CFD simulations of the batch reactor took 1.5 h on computers similar to the one reported previously and required excessive memory storage. Note that this computational cost does not account for the substantial time investment needed for the model setup and testing. Furthermore, CFD models once developed can rarely be adapted to new situations with new parameter values. More details about the CFD model used in this study are recorded in Section S6 in SI. The simulation of a CFD model (dashed line) under the high-conductivity high-zone shock fits well with the MEA sensor profiles (blue points) (Fig. 5a), while there was a large discrepancy between the CFD simulated result and the MEA sensor data points under the middle and low shock (Fig. 5b and 5c). This might be attributed to the simplification in CFD simulation for ion transport processes as it only considers ideal conditions and neglects some side-effects such as the difference in surface smoothness and difference in mixing ability in each compartment (high, middle, and low) of the batch reactor. For instance, the middle zone was assumed to have the weakest mixing ability leading to the lowest mass transfer effectiveness while the mass transfer effectiveness should be highest when the shock came from the low position closest to the mixing bar. In contrast, using the non-ideal mixing model, the SSE was reduced by 92.23% and 80.45% (Fig. 5). It should be noted that a CFD model that compartmentalizes the reactor in a similar manner to our simple non-ideal mixing model, is expected to perform much better. However, the development and

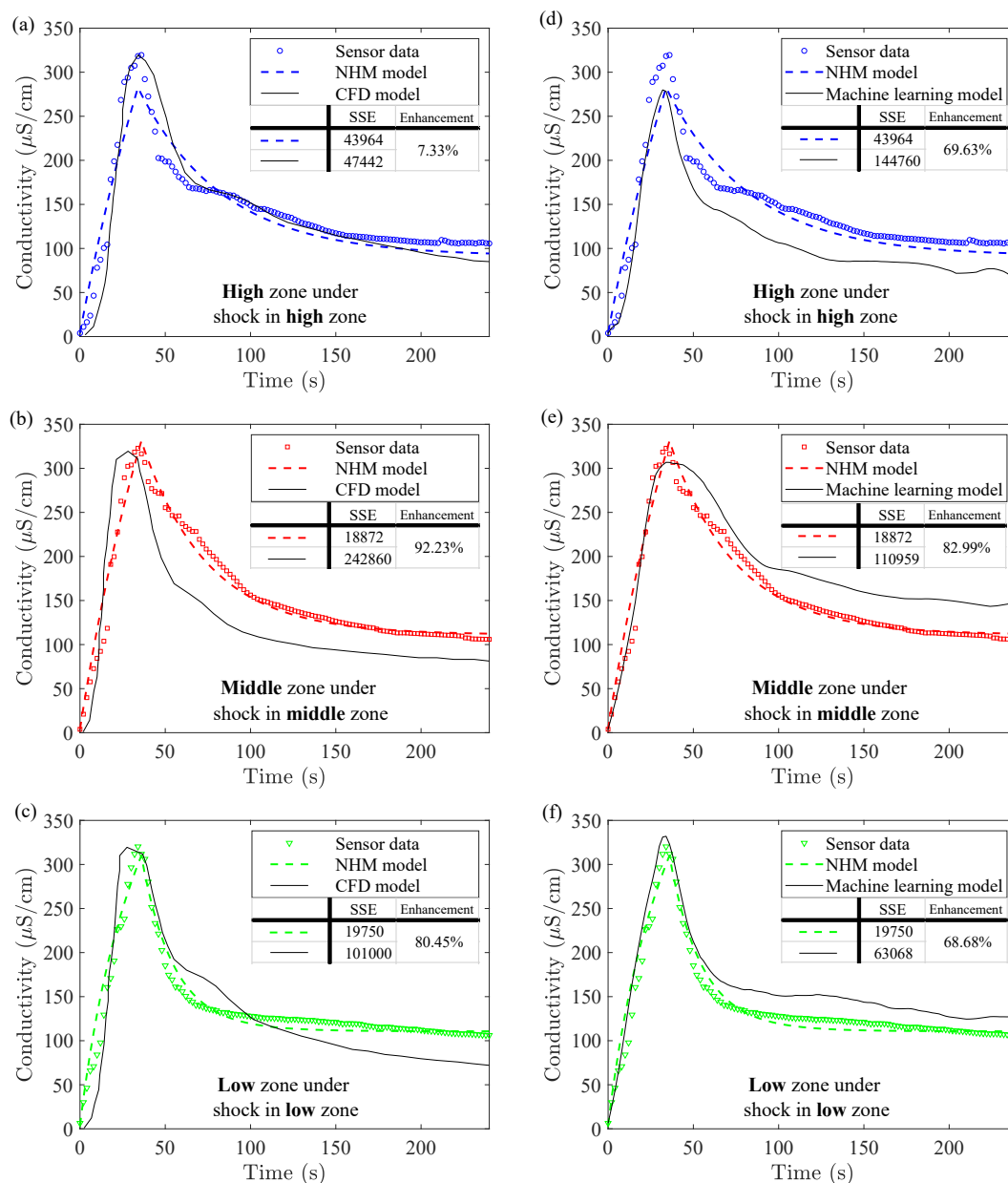


Fig. 5. Comparisons of the simulation results of the non-ideal heterogeneous mixing model (dashed line) with the fitting results of (a–c) the CFD model and with the fitting results of (d–f) the machine learning model, are plotted for each zone corresponding with the conductivity shock injection locations. (a and d: plots of the high zone under shock injected in the high zone; b and e: plots of the middle zone under shock injected in the middle zone; c and f: plots of the low zone under shock injected in the low zone). (Note: NHM = Non-ideal heterogeneous mixing; The sensor data profile (dots) and CFD model simulation are extracted from the previous study [64]).

computational costs for such a model are considered to be prohibitive for any practical, real-time implementation and use for precise control systems.

The observed mixing trends could not be represented well by the CFD simulation under conductivity shocks (Fig. 5), let alone the fast-transient scenarios of pH with multifactorial reactions. As an example, an axisymmetric model of a pH-sensitive electrochemical field effect sensor comprising 13,650 elements was deployed to simulate a geometrical domain of 0.09 mm^2 , demonstrating that it is intractable to apply CFD models in the batch reactors used in this study (volume: 380 mL) as the grid would have to be refined by a factor of 150.

The non-ideal mixing model was also compared with a pure data-driven model from the Eureka modeling engine (DataRobot), that generates differential equations trained on the same data set. All data points were equally weighted for training (detailed settings are shown in

Figure S2 in the SI) and were integrated as black lines in Fig. 5d–f. The mean SSE (full name) values between the original sensor data and machine learning results were 144760, 110959, and 63,068 for each shock (high, middle, and low locations), respectively. In contrast, the SSE value between the original sensor data and the non-ideal mixing model's simulation results were markedly lowered by 68–83%, respectively. The poor fit of the Eureka regression models is attributed to lacking the conservation principles as a basis, so that the regression models deviate from the main trends of mass and heat transfer.

3.3. Validation and calibration of sensors and Non-ideal mixing models

The non-ideal mixing models can be easily modified to simulate conductivity or pH profiles of other solute species by calibrating the parameters. In terms of conductivity, the main transport mechanism of

ions without chemical reaction should be the same. However, the uniqueness of each ion is associated with distinct conductivity values, posing the requirement for calibrating the as-developed models to sustain accuracy under varying scenarios. To further validate the applicability of the developed non-ideal heterogeneous mixing models, additional experiments were conducted by injecting different soluble compounds (KCl, MgSO_4 and NaOH). The conductivity and pH profiles were simulated versus the experimental sensor data using the corresponding models with the parameters calibrated based on the actual experimental conditions.

For validation of the conductivity model, the original optimal parameter values (as listed in Table S2 in the SI) were used to predict the KCl and MgSO_4 conductivity profiles. The results showed that the simulated profiles using the original optimal parameter values qualitatively follow the same trends as the new data (Fig. 6a and 6c). The

reason for the significant quantitative mismatch is due to the differences in injection periods between the new and the original experiments. Since all shock injections are manual operations, the injection speeds cannot be regarded as a controllable experimental condition. The high-zone data reaches a peak much faster, indicating that the injection speeds for the KCl and MgSO_4 experiments are faster than the NaCl experiment. Apart from the injection speeds, the absolute injection quantity of different ions is another attribute leading to a mismatch. For example, though the mass concentrations of KCl and MgSO_4 (200 μL , 100 g/L) injected are the same compared with the original NaCl conductivity experiment, different ions lead to different conductivities in solution and different shock conductivity C_v . The electrical conductivities of the ionic solutions based on mass percent are listed in Table S4 in the SI. Since aqueous NaCl and KCl solutions exhibit nearly the same conductivities, the predicted KCl profile using the original NaCl injection model exhibits

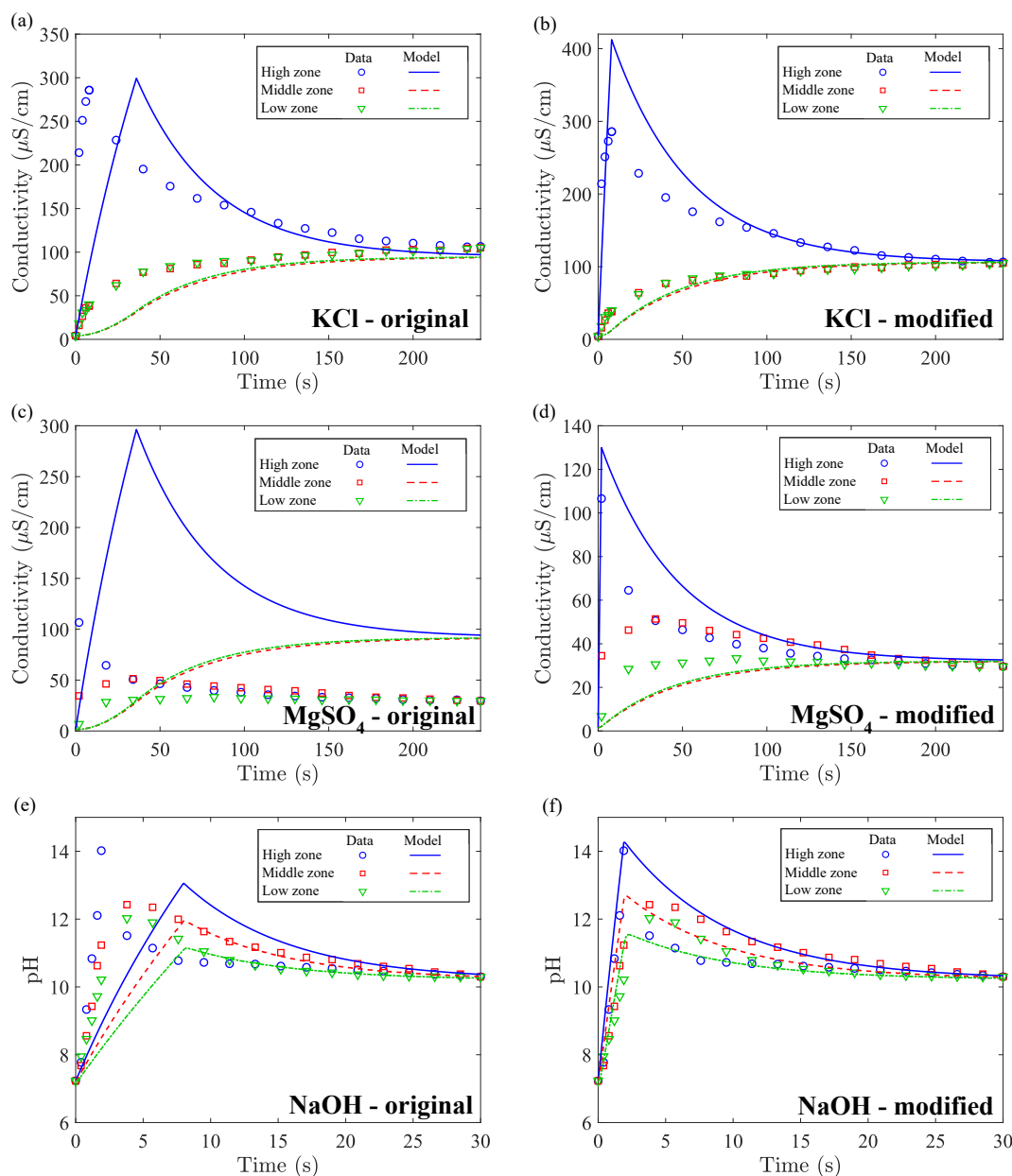


Fig. 6. The predictive simulation results are plotted for KCl conductivity profiles versus experimental data using (a) original optimal parameters and (b) modified parameters. The predictive simulation results are plotted for MgSO_4 conductivity profile versus experimental data using (c) original optimal parameters and (d) modified parameters. The predictive simulation results are plotted for NaOH pH profiles versus experimental data using (e) original optimal parameters and (f) modified parameters.

nearly the same steady-state conductivity versus the new experimental data (a). In contrast, the steady-state conductivity of the predicted MgSO_4 is around three times higher than the new experimental data (Fig. 6c). This difference is expected since MgSO_4 exhibits roughly one-third of the electrical conductivity of NaCl across the mass percentage range (Table S4 in the SI). To improve the simulation results (i.e., model prediction accuracy), a simple calibration procedure (Section S5 in the SI) was conducted without modifying the model structure, so that the underlying physical phenomena captured by the original model could be preserved. The revised conductivity profiles for KCl and MgSO_4 (Fig. 6b and 6d) exhibit substantially improved fits.

To validate the pH model for the NaOH experiment, the pH profile was simulated using the original parameters for the KOH injection case. The simulated pH profile exhibits the same qualitative behavior as the data (Fig. 6e). Again, the major mismatch is caused by the observed difference between the injection periods of the NaOH and KOH data. The time duration for the pH of the NaOH experiment to reach the peak is much shorter. Thus, the corresponding shock parameter H_v should be calibrated to mitigate this difference. The calibration process is summarized in Section S5 in the SI. The revised pH profile (Fig. 6f) exhibits a far better fit than the original simulation, where the peak pH from the model also matches the data. The profile of the high-zone pH in the short time horizon after the peak does not accurately fit the data. The probable reason is that the quasi dynamics of OH^- transport after the shock is not accurately captured by the model or the experimental errors.

3.4. Non-ideal mixing models for improved wastewater treatment with precise control

3.4.1. Simulation results for the wastewater nitrification system with Closed-Loop controls

The simulation results for each independent study are illustrated in Fig. 7. For the high-zone shock case, the PI controller begins to adjust the air valve to accelerate the airflow rate for excess ammonium removal once the disturbance occurring in the high-zone inlet flow is detected. The high-zone conductivity quickly drops below the SP, then the valve on the air stream is closed and the conductivity gradually rises towards the SP. As for middle-zone and low-zone shocks, the conductivities can still be controlled at the SP despite only using feedback readings from the high-zone sensor. The reason is that the conductivity becomes quickly mixed at around $t = 2400$ s resulting in the overall conductivity of the tank approaching the SP under control.

For comparison, the MPC simulation results are also illustrated in Fig. 7. For the high-zone shock simulation, the conductivities can be

directed to the steady state at SP much faster than PI control. As indicated by the control variable, the consumption of oxygen is reduced significantly by MPC, implying substantial energy savings. Furthermore, the middle-zone and low-zone shock simulations show that with MPC, much less ammonium is discharged to the environment than with PI control. This is because multi-input MPC can account for feedback signals from all sensors, make accurate predictions of process transients using the non-ideal heterogeneous mixing models, and take appropriate action versus the PI controller that only considers feedback signals from the high-zone sensor.

3.4.2. Evaluation of treatment performance and energy savings

An open-loop controller was also simulated for each study to represent conventional and conservative operations as a reference for comparisons. Once the shock from the influent is observed ($t = 2100$ s), the operator will open the aeration valve by an amount estimated from the difference between the shock value and SP for full oxidation (u is set as 561.44 mg/s). After the system's fixed settling time (1000 s), the operator will adjust the valve again. In contrast, for the uncontrolled simulations, the control variable is always set at the initial value ($u_0 = 168$ mg/s) which results in the steady-state effluent conductivity meeting the SP under steady influent conditions.

To evaluate the system's performance, the excess ammonium discharge was quantified as the area under the conductivity profiles as they go above the SP over the simulation horizon (2000 s). In addition, the energy consumption was quantified as the overall amount of air used for ammonium oxidation over the simulation horizon. The comparisons between uncontrolled, open-loop control, PI control, MPC, EMPC1, and EMPC2 cases are illustrated in Fig. 8 with the data values for these plots listed in Table S6 in the SI. The discharge quantification for each case is calculated as the percentage of the uncontrolled simulation, whereas the energy quantification is represented by the percentage of the open-loop control simulation. It is apparent from the discharge plot (Fig. 8a), that all the control strategies can greatly reduce the discharge compared with uncontrolled simulations. MPC and both EMPC strategies perform much better than PI control as less ammonium is discharged into the environment. This is especially clear for the middle- and low-zone shock studies, where MPC and EMPC account for multiple input measurements simultaneously, while PI control can only account for the high-zone measurement. Specifically, EMPC1 has the best performance for reducing discharge, coinciding with its underlying design objective. On the other hand, energy usage (Fig. 8b) under PI control, MPC, and both EMPC strategies, is reduced versus open-loop control. As for the high-zone shock injection study, MPC has the greatest advantage

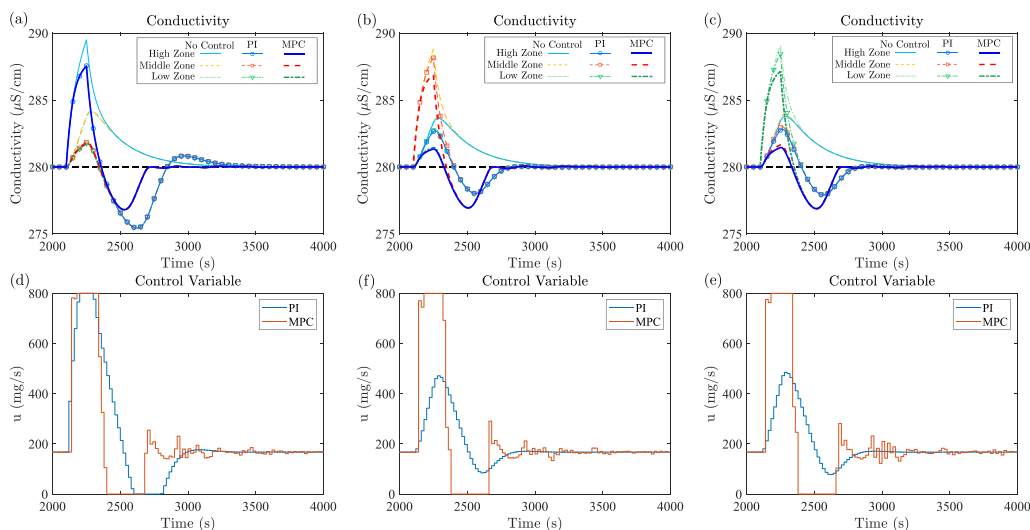


Fig. 7. The conductivity profiles are plotted for the uncontrolled, PI control, and MPC simulations for independent studies with NH_4Cl conductivity shock (320 $\mu\text{S/cm}$) continuously injected from 2100 s to 2250 s, respectively, in the (a) high, (b) middle, and (c) low zones of a continuous-flow nitrification system. The PI (blue) and MPC (orange) control actions for the (d) high-zone shock case, (e) middle-zone shock case, and (f) low-zone shock case, are presented below their corresponding conductivity profiles.

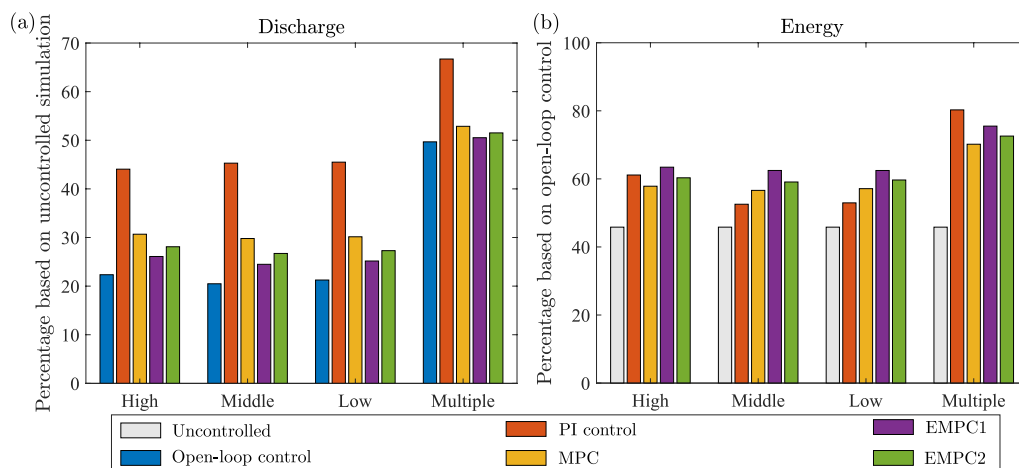


Fig. 8. (a) The overall discharge of NH_4Cl above the setpoint (SP) over the simulation horizon, is plotted for each control scenario as a percentage normalized against the uncontrolled case (the uncontrolled case is 100%). (b) The total compressed air consumption (equating to energy usage) over the simulation horizon is plotted for each control scenario as a percentage normalized against the open-loop control simulation (the open-loop control case is 100%). The labels “High”, “Middle”, “Low”, and “Multiple” represent high-zone, middle-zone, low-zone, and multiple-zone shocks, respectively. In both cases, lower percentages equate to better performance.

due to the least energy usage among other control strategies while its discharge is only slightly higher than EMPC1 and EMPC2. As for the middle- and low-zone shock studies, PI control saves the most energy, but also has the greatest discharge compared with the other strategies.

It is observed that MPC has lower energy usage compared with EMPC1 and EMPC2. EMPC1 is formulated to minimize environmental discharge and it is apparent that more energy is consumed to achieve this objective. EMPC2 is formulated to minimize air consumption with constraints on discharge, but as indicated, it still consumes slightly more energy than MPC. The reason for this behavior is that EMPC2 seeks a control setting that has the lowest energy consumption with a prerequisite to strictly satisfy the discharge constraints while MPC only minimizes the errors without any specifications on discharge.

For the multiple shocks study, barring open-loop control, PI control is apparently the worst control strategy using the most energy and resulting in the most ammonium discharge. The energy usage and discharge for MPC, EMPC1, and EMPC2 are relatively similar, and any lower discharge observed must be paid for with greater energy consumption. It is suggested that for real-world operation, control strategies should be determined based on the specific conditions of the WTP/WWTP. This is aligned with the notion of “smart plant operations,” where process control, plant-wide management, and corporate office systems communicate in real-time through networks to satisfy targeted economic, environmental, and safety performance objectives [62]. As a result, the developed conductivity model, modified for continuous flow is valid for MPC and EMPC, and promising for real-time decision-making over the network for better management, energy savings, and handling of market/demand changes in WTPs/WWTPs.

4. Conclusions

WTP/WWTPs have been well-known for their large amounts of data generated with low efficiency of data utilization, operational uncertainty, and fluctuations in water quality/quantity [18,19]. These fluctuations require frequent parameter adjustment and model recalibration during operation for effective MPC, but traditional physics-based mechanistic models are incapable of adapting to these changes in a timely manner [63]. The non-ideal heterogeneous mixing models proposed in this study are simple with few fitting parameters and take much less time for simulation than traditional CFD models. The collected high-resolution sensor data can be instantly transmitted to the model calibration process, ensuring the calibration of non-ideal heterogeneous mixing models in a real-time *in situ* mode during on-going operation.

This unique feature mitigates the severe time-delay problems of traditional pure physics-based models and enables a prompt modification for higher accuracy system identification based on authentic representations of the system. Exploiting this technology within closed-loop control, such as MPC, enables a novel precise control system for WTP/WWTPs.

Moreover, the heterogeneity profiling models can be applied for pattern recognition so as to better understand the internal mechanisms of complex processes (e.g., transport mechanisms of different ions), with or without involving algorithms and redundant equation deduction. Such generalized methodology can serve as a platform for simulating state variables for other chemical species with similar physical principles.

Declaration of Competing Interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

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Appendix A. Supplementary data

Supplementary data to this article can be found online at <https://doi.org/10.1016/j.cej.2021.132819>.

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