

COMPUTER SURROGATE MODEL TO PREDICT THE SINGLE-PHASE MIXING QUALITY IN STEADY STATE MIXING TANKS**CROSS-REFERENCE TO RELATED APPLICATIONS**

[0001] This application claims priority to Provisional Application No. 63/117,789, entitled "COMPUTER SURROGATE MODEL TO PREDICT THE SINGLE-PHASE MIXING QUALITY IN STEADY STATE MIXING TANKS", filed November 24, 2020, the disclosure of which is incorporated herein by reference in its entirety.

FIELD OF THE DISCLOSURE

[0002] The present disclosure generally relates to training a surrogate machine learning model to predict mixing quality.

BACKGROUND

[0003] Mixing is a critical step in developing drug substances. Low quality of mixing may lead to out-of-specification downstream drug substance and/or wasted capital during the operation. High levels of mixing are required to ensure downstream product quality. This is achieved by mixing inlet streams (e.g. buffer flow, retentate flow, etc.) in a tank while continuously stirring the tank at constant speed using an agitator. The resulting volume exits the tank and goes to the subsequent steps. Several configurations are usually utilized to enhance the degree of mixing such as use of internal baffles, placing the agitator at an angle to the tank, use of tangential or radial blades and so on. The quality of mixing, usually represented by "standard deviation" of trace concentration in the tank and in the tank exit, is a complex relationship of tank geometry, working volume, inlet and outlet configuration and flow rates, agitation speed and drug substance properties that is typically realized only after long and expensive in-situ studies. In-silico models based on computational fluid dynamics (CFD) have been used in order to reduce the cost and time associated with these studies; however, while resulting in reduced experimentations, CFD modeling is processor-intensive, time consuming, and sometimes expensive (e.g., if third party vendors are required).

SUMMARY

[0004] The present disclosure provides a surrogate model to predict the quality of mixing at steady state condition with the ability to vary all the input parameters, without expensive and time-consuming computational fluid dynamics (CFD) simulations. Surrogate modeling is a novel predictive tool that provides an understanding of mixing qualities in agitated tanks. The surrogate model can be used to predict the best working volume and impeller speed for a certain operation and significantly reduce the characterization time. The surrogate model provided herein allows for consistent and reliable prediction of mixing characteristics of a mixing process, helping to ensure supply to every patient every time. The surrogate model also allows engineering teams to make rapid and reliable science-based decisions when selecting and recommending a mixing system for a given product, following a right first time (predict and prevent) development philosophy. Moreover, compared to time consuming and computationally intensive CFD modeling, the surrogate model provided herein can output instant results responsive to changes in process variables (flowrates, mixer RPM, fluid properties, etc.).

[0005] Advantageously, predictions using the surrogate model provided herein provide immediate insight into the mixing quality, with the flexibility of assessing any combination of variables, without expensive and time-consuming CFD or in-situ studies. Moreover, by making predictions using the surrogate model, significant time and money can be saved due to reduced third party involvement.

[0006] In an aspect, a method is provided, comprising: generating, by one or more processors, a plurality of training CFD models for a plurality of training steady state mixing configurations in which inlet streams are mixed in tanks, wherein each training CFD model is generated based on a plurality of steady state mixing factors associated with each training steady state mixing configuration; calculating, by the one or more processors, a mixing quality for each training steady state mixing configuration using each respective training CFD model; generating, by the one or more processors, a training dataset that includes the steady state mixing factors associated with each training steady state mixing configuration, and the calculated mixing quality for each training steady state mixing configuration; and training, by the one or more processors, a machine learning model, using the training dataset, to predict mixing qualities for steady state mixing configurations based on based on steady state mixing factors associated with the steady state mixing configurations.

[0007] In another aspect, a computer system is provided, comprising: one or more processors; and a non-transitory program memory communicatively coupled to the one or more processors and storing executable instructions that, when executed by the one or more processors, cause the processors to: generate a plurality of training CFD models for a plurality of training steady state mixing configurations in which inlet streams are mixed in tanks, wherein each training CFD model is generated based on a plurality of steady state mixing factors associated with each training steady state mixing configuration; calculate a mixing quality for each training steady state mixing configuration using each respective training CFD model; generate a training dataset that includes the steady state mixing factors associated with each training steady state mixing configuration, and the calculated mixing quality for each training steady state mixing configuration; and train a machine learning model, using the training dataset, to predict mixing qualities for steady state mixing configurations based on based on steady state mixing factors associated with the steady state mixing configurations.

[0008] In still another aspect, a non-transitory computer readable storage medium storing computer-readable instructions that, when executed by one or more processors, cause the one or more processors to: generate a plurality of training CFD models for a plurality of training steady state mixing configurations in which inlet streams are mixed in tanks, wherein each training CFD model is generated based on a plurality of steady state mixing factors associated with each training steady state mixing configuration; calculate a mixing quality for each training steady state mixing configuration using each respective training CFD model; generate a training dataset that includes the steady state mixing factors associated with each training steady state mixing configuration, and the calculated mixing quality for each training steady state mixing configuration; and train a machine learning model, using the training dataset, to predict mixing qualities for steady state mixing configurations based on based on steady state mixing factors associated with the steady state mixing configurations.

BRIEF DESCRIPTION OF THE DRAWINGS

[0009] FIG. 1 illustrates an example steady-state mixing tank in which the systems and methods described herein may be implemented, in some examples.

[0010] FIG. 2 illustrates relationships between various steady state mixing factors used in training a surrogate machine learning model to predict mixing quality, in accordance with some examples described herein.

[0011] FIG. 3 illustrates a flow diagram of an example method of training a surrogate machine learning model to predict mixing quality in a steady-state mixing tank, in accordance with some examples described herein.

[0012] FIG. 4A illustrates actual test data and predicted test data for a linear regression surrogate model for predicting mixing quality in a steady-state mixing tank, and FIG. 4B illustrates actual test data and predicted test data for a neural network regression surrogate model for predicting mixing quality in a steady-state mixing tank, in accordance with some examples described herein.

[0013] FIG. 5A illustrates changes in the coefficient of determination for training data and testing data based on the number of cases used in training a linear regression surrogate model to predict mixing quality in a steady-state mixing tank, and FIG. 5B illustrates changes in the coefficient of determination for training data and testing data based on the number of cases used in training a neural network regression surrogate model to predict mixing quality in a steady-state mixing tank, in accordance with some examples described herein.

[0014] FIG. 6 illustrates the standard deviations predicted by a computational fluid dynamics (CFD) model compared to the standard deviations predicted by a surrogate model trained to predict mixing quality in a steady-state mixing tank for various numbers of cases, in accordance with some examples described herein.

[0015] FIG. 7 illustrates a block diagram of an example system for training a surrogate machine learning model to predict mixing quality in a steady-state mixing tank, in accordance with some examples described herein.

[0016] FIG. 8 illustrates a schematic diagram of example inputs and outputs used to train a surrogate machine learning model to predict mixing quality in a steady-state mixing tank, in accordance with some examples described herein.

[0017] FIG. 9 illustrates a flow diagram of an example method for training a surrogate machine learning model to predict mixing quality in a steady-state mixing tank, in accordance with some examples described herein.

DETAILED DESCRIPTION

[0018] Referring now to the drawings, FIG. 1 illustrates an example steady-state mixing tank 100 in which the systems and methods described herein may be implemented, in some examples. As shown in FIG. 1, the working volume 102 of the tank 100 is not the entire volume of the tank 100. The tank 100 includes one or more diverter plates 104, a vortex breaker 106, an impeller 108, a buffer inlet 110, a TFF exit 112, and a retentate inlet 114.

[0019] FIG. 2 illustrates relationships between various steady state mixing factors used in training a surrogate machine learning model to predict mixing quality, in accordance with some examples described herein. As shown in FIG. 3, the steady state mixing factors include volume (L), speed (rpm), tangential flow filtration, or TFF (in liters per minute, or LPM), retentate (LPM), equipment (i.e., an integer number to distinguish between different tanks or impellers having different sizes, shapes, and/or purposes), and standard deviation. The steady state mixing factors may include additional or alternative measurements in various examples. As shown in FIG. 2, any relationship between the steady state mixing factors and one another, and any relationship between each steady state mixing factor and the response (i.e., the measures of mixing quality) is generally not visually discernable. Accordingly, as discussed in greater detail below, a machine learning approach may be used to generalize possible relationships that are not easily visibly discernable.

[0020] FIG. 3 illustrates a flow diagram of an example method of training a surrogate machine learning model to predict mixing quality in a steady-state mixing tank, in accordance with some examples described herein. During the process of constructing the

surrogate model based on deep learning techniques, the following steps are taken, as shown at FIG. 3. First, a random seed may be set to ensure repeatability of the results. Next, total available CFD runs may be divided to a train (90%) and test set (10%) randomly but the splitting process is stratified by making sure both standard deviation > 1 (short circuiting) and standard deviation < 1 (plug flow behavior) is represented in both sets equally.

[0021] The training set may then be used to calibrate (train) the model. At steady state (number of inlets + number of outlets - 1), independent flowrates may be used as numerical features. In addition, impeller speed, tank working volume, and fluid Reynolds number may be used as numerical features. The tank and stirrer geometries may be used as categorical features. On the other hand, the values of standard deviation of mean age may be used as numerical labels. A polynomial combination up to order 9 may be added to the numerical features, and the input data may be normalized using a normal distribution with mean of zero and standard deviation of one. A multi-layer perceptron (MLP) neural network may then be constructed with several possible layer sizes, learning rates and L2 regularizer coefficients. Additionally, a grid search model may be built using a cross-validation method to find the best model parameters using the training set. This will ensure the most reliable calibrated model by cross-validating all the parameters on the training set. The best validated model result may then be applied to the test set to report the model quality, including mean absolute error.

[0022] FIG. 4A illustrates actual test data and predicted test data for a linear regression surrogate model (based on Ridge regression methodology) for predicting mixing quality in a steady-state mixing tank, and FIG. 4B illustrates actual test data and predicted test data for a neural network regression surrogate model (specifically, an Artificial Deep Neural Network) for predicting mixing quality in a steady-state mixing tank, in accordance with some examples described herein. As shown in FIG. 4B as compared to FIG. 4A, the neural network regression surrogate model generally predicts the standard deviation of the mean age more accurately than the linear regression surrogate model.

[0023] FIG. 5A illustrates changes in the coefficient of determination for training data and testing data based on the number of cases used in training a linear regression surrogate model (e.g., the linear regression surrogate model discussed with respect to FIG. 4A) to predict mixing quality in a steady-state mixing tank, and FIG. 5B illustrates changes in the coefficient of determination for training data and testing data based on the number of cases used in training a neural network regression surrogate model (e.g., the neural network regression surrogate model discussed with respect to FIG. 4B) to predict mixing quality in a steady-state mixing tank, in accordance with some examples described herein. FIG. 6 illustrates the standard deviations predicted by a computational fluid dynamics (CFD) model compared to the standard deviations predicted by a surrogate model trained to predict mixing quality in a steady-state mixing tank for various numbers of cases, in accordance with some examples described herein. Predictions of the artificial deep neural network surrogate model are shown as blue circles and they correspond to cases for which the response (i.e., the measure of mixing quality) was known, shown as orange crosses, as well as cases for which the response was not known, where the surrogate model was used to predict the response.

[0024] FIG. 7 illustrates a block diagram of an example system 700 for training a surrogate machine learning model to predict mixing quality in a steady-state mixing tank, in accordance with some examples described herein. The high-level architecture illustrated in FIG. 7 may include both hardware and software applications, as well as various data communications channels for communicating data between the various hardware and software components, as is described below.

[0025] The system 700 may include a computational fluid dynamics (CFD) computing device 702, and a surrogate model computing device 704, as well as one or more other computing devices 706 in some examples. The computing devices 702, 704, and 706 may communicate with one another via a network 708, which may be a wired or wireless network.

[0026] Generally speaking, the CFD computing device 702 may include one or more processors 710 and a memory 712 (e.g., volatile memory, non-volatile memory) accessible by the one or more processors 710 (e.g., via a memory controller). The one or more processors 710 may interact with the memory 712 to obtain, for example, computer-readable instructions stored in the memory 712. The computer-readable instructions stored in the memory 712 may cause the one or more processors 710 to execute one or more applications, including a CFD modeling application 714. Executing the CFD modeling application may include receiving steady state mixing factors associated with a plurality of various steady state mixing configurations, generating CFD models for each of the steady state mixing configurations based on the steady state mixing factors, and calculating a measure of mixing quality for each steady state mixing configuration based on CFD model for each steady state mixing configuration. Executing the CFD modeling application may further include storing the determined measurements of mixing quality and CFD models for each steady state mixing configuration in a training CFD model database 716 and/or a test CFD model database 718. For instance, in some examples, 90% of the data generated by the CFD modeling application 714 may be stored in the training CFD model database 716 while 10% of the data generated by the CFD modeling application is stored in the test CFD model database 718. In other examples, different percentages of the data generated by the CFD modeling application 714 may be stored in each of the databases 714 and 716, or all of the data generated by the CFD modeling application 714 may be stored in the training CFD model database 716. Furthermore, in some examples, the computer-readable instructions stored on the memory 712 may include instructions for carrying out any of the steps of the method 900, described in greater detail below with respect to FIG. 9.

[0027] Generally speaking, the surrogate model computing device 704 may include one or more processors 720 and a memory 722 (e.g., volatile memory, non-volatile memory) accessible by the one or more processors 720 (e.g., via a memory controller). The one or more processors 720 may interact with the memory 722 to obtain, for example, computer-readable instructions stored in the memory 722. The computer-readable instructions stored in the memory 722 may cause the one or more processors 720 to execute one or more applications, including a surrogate model training application 724, a surrogate machine learning model 726, and a steady state mixing quality predictor application 728. Executing the surrogate model training application 724 may include accessing the training CFD model database 716 and using the steady state mixing factors and calculated measure of mixing quality for each steady state mixing configuration as training data to train a surrogate machine learning model 726 to predict mixing quality based on steady state mixing factors for a given steady state mixing configuration, as discussed in greater detail with respect to FIG. 8, below. Executing the steady state mixing quality predictor application 728 may include applying the trained surrogate machine learning model 726 to a new steady state mixing configuration in order to predict a measure of mixing quality for the new steady state mixing configuration. Additionally, in some examples, the computer-readable instructions stored in the memory 722 may further include instructions for accessing the test CFD model database 718 and testing the trained surrogate machine learning model 726 against the test CFD model data. For instance, the measure of mixing quality for a given steady state configuration calculated by the CFD modeling application 714 and stored in the test CFD model database may be compared to a measure of mixing quality predicted for the same steady state configuration using the trained surrogate machine learning model 726 to determine a measure of the accuracy

of the trained machine learning model 726. Furthermore, the computer-readable instructions stored on the memory 722 may include instructions for carrying out any of the steps of the method 900, described in greater detail below with respect to FIG. 9.

[0028] In examples in which other computing devices 706 are included in the system 700, these other computing devices 706 may each include one or more processors 730 and a memory 732 (e.g., volatile memory, non-volatile memory) accessible by the one or more processors 730 (e.g., via a memory controller). The one or more processors 730 may interact with the memory 732 to obtain, for example, computer-readable instructions stored in the memory 732. The computer-readable instructions stored in the memory 732 may cause the one or more processors 730 to receive steady state mixing factors for a given steady state mixing configuration, send the steady state mixing factors for the given steady state mixing factor configuration to the surrogate model computing device 704, and receive a predicted measure of mixing quality from the surrogate model computing device 704 (i.e., based on steady state mixing quality predictor application 728 of the surrogate model computing device 704 applying the trained surrogate machine learning model 726 to the steady state mixing factors from the other computing device 706). Furthermore, in some examples, the computer-readable instructions stored on the memory 732 may include instructions for carrying out any of the steps of the method 900, described in greater detail below with respect to FIG. 9.

[0029] Now referring to FIG. 8, as discussed above, the surrogate model training application 724 may train the surrogate machine learning model 726 in accordance with the scheme 800, and the steady state mixing quality predictor application 728 may operate the trained surrogate machine learning model 726 in accordance with the scheme 800.

[0030] The surrogate model training application 724 can receive various input signals, including steady state mixing factors 802 for a new steady state mixing configuration (i.e., for which a mixing quality is to be predicted), as well as training data 804 generated using CFD models for a plurality of training steady state mixing configurations. The training data 804 may include training steady state mixing factors 806 for each training steady state mixing configuration, as well as training measurements of mixing quality 808 for each training steady state mixing configuration as calculated using CFD models. The steady state mixing factors 802 and 806 may include one or more of: tank geometry, stirrer geometry, working volume, inlet configuration, outlet configuration, inlet flow rates for each inlet, outlet flow rates for each outlet, agitation speed, impeller speed, fluid Reynolds number for each substance, and/or other chemical and pharmaceutical properties for each substance involved in the mixing, or any other suitable steady state mixing factors associated with each steady state mixing configuration in which inlet streams are mixed in a tank. The training measurements of mixing quality 808 calculated using the CFD models may include measures of the standard deviation of trace concentration in the tank for each steady state mixing configuration, or any other suitable measure of mixing quality for each steady state mixing configuration.

[0031] Generally speaking, the feature extraction functions 810 can operate on at least some of these input signals to generate feature vectors, or logical groupings of parameters associated with various steady state mixing factors for each steady state mixing configuration. For example, the feature extraction functions 810 may generate a feature vector that indicates that for a higher agitation speed, the result corresponds to a higher quality of mixing. As another example, the feature extraction functions 810 may generate a feature vector that indicates that when working volume is increased for substances having certain chemical or pharmaceutical properties, the result corresponds to a lower quality of mixing. These results can be used as a set of labels for the feature vectors.

[0032] Accordingly, the feature extraction functions 810 can generate feature vectors 812 using the training steady state mixing factors 806 for each training steady state mixing configuration and the training measurements of mixing quality 808 for each training steady state mixing configuration, as calculated using CFD models. In general, the surrogate model training application 724 can train the surrogate machine learning model 726 using supervised learning, unsupervised learning, reinforcement learning, or any other suitable technique. Moreover, the surrogate model training application 724 can train the surrogate machine learning model 726 as a standard regression model.

[0033] Over time, as the surrogate model training application 724 trains the surrogate machine learning model 726, the trained surrogate machine learning model 726 may learn to predict a measure of mixing quality 814 for a given steady state mixing configuration based on steady state mixing factors 802 associated with the steady state mixing configuration. For instance steady state mixing quality predictor application 728 may receive steady state mixing factors 802 for a new steady state mixing configuration as inputs (e.g., via a user interface of the surrogate model computing device 704), and may apply the trained surrogate machine learning model 726 to the steady state mixing factors 802 for the new steady state mixing configuration. The trained surrogate machine learning model 726 may then generate a predicted steady state mixing quality 814 for the new steady state mixing configuration using the steady state mixing factors 802, and may send an indication of the predicted measure of mixing quality 814 to the steady state mixing quality predictor application 728, which may display the predicted measure of mixing quality 814 to a user, or may send the predicted measure of mixing quality 814 to another device (such as the other computing device 706), or may store the predicted measure of mixing quality 814, etc.

[0034] In some examples, a CFD model may be generated for a testing steady state mixing configuration using the steady state mixing factors of the testing steady state mixing configuration, and the CFD model may calculate a mixing quality for the testing steady state mixing configuration. The trained surrogate machine learning model 726 may then be applied to the steady state mixing factors of the testing steady state mixing configuration, and may predict a measure of mixing quality using the steady state mixing factors of the testing steady state mixing configuration. This predicted measure of mixing quality may then be compared to the measure of mixing quality calculated for the same testing steady state mixing configuration by the CFD model. Any difference between the predicted and calculated measure of mixing quality may be used in subsequent training of the surrogate machine learning model 726, *i.e.*, for fine-tuning to improve the performance of the surrogate machine learning model 726.

[0035] FIG. 9 illustrates a flow diagram of an example method 900 for training a surrogate machine learning model to predict mixing quality in a steady-state mixing tank, in accordance with some examples described herein. One or more steps of the method 900 may be implemented as a set of instructions stored on a computer-readable memory (e.g., memories 712, 722, and/or 732) and executable on one or more processors (e.g., processors 710, 720, and/or 730).

[0036] The method may begin when a plurality of training CFD models are generated (block 902) for a plurality of training steady state mixing configurations in which inlet streams are mixed in tanks. Each training CFD model may be generated based on a plurality of steady state mixing factors associated with each training steady state mixing configuration. For instance, the steady state mixing factors may include one or more of: tank geometry, stirrer geometry, working volume, inlet configuration, outlet configuration, inlet flow rates for each inlet, outlet flow rates for each outlet, agitation speed, impeller speed, fluid Reynolds number for each

substance, and/or other chemical and pharmaceutical properties for each substance involved in the mixing, or any other suitable steady state mixing factors associated with a given steady state mixing configuration in which inlet streams are mixed in a tank.

[0037] A mixing quality may be calculated (block 904) for each steady state mixing configuration using each respective training CFD model. For instance, the mixing quality may be a measure of the standard deviation of trace concentration in the tank.

[0038] A training dataset that includes the steady state mixing factors associated with each training steady state mixing configuration, and the calculated mixing quality for each training steady state mixing configuration may be generated (block 906).

[0039] Using the training dataset, a machine learning model may be trained (block 908) to predict mixing qualities for steady state mixing configurations based on based on steady state mixing factors associated with the steady state mixing configurations. In some examples, the machine learning model may be a deep learning model.

[0040] In some examples, the method 900 may additionally include applying (block 910) the trained machine learning model to new steady state mixing factors associated with a new steady state mixing configuration; and predicting (block 912) a mixing quality for the new steady state mixing configuration based on applying the trained machine learning model to the steady state mixing factors associated with the new steady state mixing configuration.

[0041] Additionally, in some examples, the method 900 may further include generating at least one testing CFD model for a testing steady state mixing configuration in which inlet streams are mixed in a tank. Like the plurality of training CFD models generated at block 902, the testing CFD model may be generated based on a plurality of steady state mixing factors associated with the testing steady state mixing configuration. A mixing quality may then be calculated for the testing steady state mixing configuration using the testing CFD model. The machine learning model trained at block 908 may then be applied to the steady state mixing factors associated with the testing steady state mixing configuration, and a quality of mixing may be predicted for the testing steady state mixing configuration using the trained machine learning model. The trained machine learning model may then be evaluated based on comparing the mixing quality calculated for the testing steady state mixing configuration using the testing CFD model to the mixing quality predicted for the testing steady state mixing configuration using the trained machine learning model. For instance, the trained machine learning model may be evaluated based on how closely the mixing quality calculated by the testing CFD model for the testing steady state mixing configuration matches the mixing quality predicted by the trained machine learning model for the testing steady state mixing configuration. In some examples the trained machine learning model may be modified based on the evaluation, *e.g.*, if the predicted mixing quality differs from the calculated mixing quality by greater than a threshold amount.

ASPECTS

[0042] Embodiments of the techniques described in the present disclosure may include any number of the following aspects, either alone or combination:

[0043] 1. A method, comprising: generating, by one or more processors, a plurality of training computational fluid dynamic (CFD) models for a plurality of training steady state mixing configurations in which inlet streams are mixed in tanks, wherein each training CFD model is generated based on a plurality of steady state mixing factors associated with each training steady state mixing configuration; calculating, by the one or more processors, a mixing quality for each training steady state mixing configuration using each respective training CFD model; generating, by the one or more processors, a training dataset that includes the steady state

mixing factors associated with each training steady state mixing configuration, and the calculated mixing quality for each training steady state mixing configuration; and training, by the one or more processors, a machine learning model, using the training dataset, to predict mixing qualities for steady state mixing configurations based on based on steady state mixing factors associated with the steady state mixing configurations.

[0044] 2. The method of aspect 1, further comprising: applying, by the one or more processors, the trained machine learning model to new steady state mixing factors associated with a new steady state mixing configuration; and predicting, by the one or more processors, based on applying the trained machine learning model to the steady state mixing factors associated with the new steady state mixing configuration, a mixing quality for the new steady state mixing configuration.

[0045] 3. The method of any of aspects 1 or 2, wherein the steady state mixing factors include one or more of: tank geometry, stirrer geometry, working volume, inlet configuration, outlet configuration, inlet flow rates for each inlet, outlet flow rates for each outlet, agitation speed, impeller speed, fluid Reynolds number for each substance, and other chemical and pharmaceutical properties for each substance.

[0046] 4. The method of any of aspects 1-3, wherein the mixing quality is a measure of standard deviation of trace concentration in the tank.

[0047] 5. The method of any of aspects 1-4, further comprising: generating, by the one or more processors, a testing computational fluid dynamic (CFD) model for a testing steady state mixing configuration in which inlet streams are mixed in tanks, wherein the testing CFD model is generated based on a plurality of steady state mixing factors associated with the testing steady state mixing configuration; calculating, by the one or more processors, a mixing quality for the testing steady state mixing configuration using the testing CFD model; applying, by the one or more processors, the trained machine learning model to the steady state mixing factors associated with the testing steady state mixing configuration; predicting, by the one or more processors, based on applying the trained machine learning model to the steady state mixing factors associated with the testing steady state mixing configuration, a quality of mixing for the testing steady state mixing configuration; and evaluating, by the one or more processors, the trained machine learning model by comparing the mixing quality calculated for the testing steady state mixing configuration using the testing CFD model and the mixing quality predicted for the testing steady state mixing configuration using the trained machine learning model.

[0048] 6. The method of any of aspects 1-5, wherein the machine learning model is a deep learning model.

[0049] 7. A computer system, comprising: one or more processors; and a non-transitory program memory communicatively coupled to the one or more processors and storing executable instructions that, when executed by the one or more processors, cause the processors to: generate a plurality of training computational fluid dynamic (CFD) models for a plurality of training steady state mixing configurations in which inlet streams are mixed in tanks, wherein each training CFD model is generated based on a plurality of steady state mixing factors associated with each training steady state mixing configuration; calculate a mixing quality for each training steady state mixing configuration using each respective training CFD model; generate a training dataset that includes the steady state mixing factors associated with each training steady state mixing configuration, and the calculated mixing quality for each training steady state mixing configuration; and train a machine learning model, using the training dataset, to predict mixing qualities for steady state mixing configurations based on based on steady state mixing factors associated with the steady state mixing configurations.

[0050] 8. The computer system of aspect 7, wherein a first set of one or more processors, of the one or more processors, generate the plurality of training computational fluid dynamic (CFD) models, and wherein a second set of one or more processors, of the one or more processors, train the machine learning model.

[0051] 9. The computer system of any of aspects 7 or 8, wherein the executable instructions, when executed by the one or more processors, further cause the processors to: apply the trained machine learning model to new steady state mixing factors associated with a new steady state mixing configuration; and predict, based on applying the trained machine learning model to the steady state mixing factors associated with the new steady state mixing configuration, a mixing quality for the new steady state mixing configuration.

[0052] 10. The computer system of aspect 9, wherein a third set of one or more processors, of the one or more processors, apply the trained machine learning model to the new steady state mixing factors associated with the new steady state mixing configuration and predict the mixing quality for the new steady state mixing configuration.

[0053] 11. The computer system of any of aspects 7-10, wherein the steady state mixing factors include one or more of: tank geometry, stirrer geometry, working volume, inlet configuration, outlet configuration, inlet flow rates for each inlet, outlet flow rates for each outlet, agitation speed, impeller speed, fluid Reynolds number for each substance, and other chemical and pharmaceutical properties for each substance.

[0054] 12. The computer system of any of aspects 7-11, wherein the mixing quality is a measure of standard deviation of trace concentration in the tank.

[0055] 13. The computer system of any of aspects 7-12, wherein the executable instructions, when executed by the one or more processors, further cause the processors to: generate a testing computational fluid dynamic (CFD) model for a testing steady state mixing configuration in which inlet streams are mixed in tanks, wherein the testing CFD model is generated based on a plurality of steady state mixing factors associated with the testing steady state mixing configuration; calculate a mixing quality for the testing steady state mixing configuration using the testing CFD model; apply the trained machine learning model to the steady state mixing factors associated with the testing steady state mixing configuration; predict, based on applying the trained machine learning model to the steady state mixing factors associated with the testing steady state mixing configuration, a quality of mixing for the testing steady state mixing configuration; and evaluate the trained machine learning model by comparing the mixing quality calculated for the testing steady state mixing configuration using the testing CFD model and the mixing quality predicted for the testing steady state mixing configuration using the trained machine learning model.

[0056] 14. The computer system of any of aspects 7-13, wherein the machine learning model is a deep learning model.

[0057] 15. A non-transitory computer readable storage medium storing computer-readable instructions that, when executed by one or more processors, cause the one or more processors to: generate a plurality of training computational fluid dynamic (CFD) models for a plurality of training steady state mixing configurations in which inlet streams are mixed in tanks, wherein each training CFD model is generated based on a plurality of steady state mixing factors associated with each training steady state mixing configuration; calculate a mixing quality for each training steady state mixing configuration using each respective training CFD model; generate a training dataset that includes the steady state mixing factors associated with each training steady state mixing

configuration, and the calculated mixing quality for each training steady state mixing configuration; and train a machine learning model, using the training dataset, to predict mixing qualities for steady state mixing configurations based on based on steady state mixing factors associated with the steady state mixing configurations.

[0058] 16. The non-transitory computer readable storage medium of aspect 15, wherein the computer-readable instructions, when executed by the one or more processors, further cause the processors to: apply the trained machine learning model to new steady state mixing factors associated with a new steady state mixing configuration; and predict, based on applying the trained machine learning model to the steady state mixing factors associated with the new steady state mixing configuration, a mixing quality for the new steady state mixing configuration.

[0059] 17. The non-transitory computer readable storage medium of any of aspects 15 or 16, wherein the steady state mixing factors include one or more of: tank geometry, stirrer geometry, working volume, inlet configuration, outlet configuration, inlet flow rates for each inlet, outlet flow rates for each outlet, agitation speed, impeller speed, fluid Reynolds number for each substance, and other chemical and pharmaceutical properties for each substance.

[0060] 18. The non-transitory computer readable storage medium of any of aspects 15-17, wherein the mixing quality is a measure of standard deviation of trace concentration in the tank.

[0061] 19. The non-transitory computer readable storage medium of any of aspects 15-18, wherein the computer-readable instructions, when executed by the one or more processors, further cause the processors to: generate a testing computational fluid dynamic (CFD) model for a testing steady state mixing configuration in which inlet streams are mixed in tanks, wherein the testing CFD model is generated based on a plurality of steady state mixing factors associated with the testing steady state mixing configuration; calculate a mixing quality for the testing steady state mixing configuration using the testing CFD model; apply the trained machine learning model to the steady state mixing factors associated with the testing steady state mixing configuration; predict, based on applying the trained machine learning model to the steady state mixing factors associated with the testing steady state mixing configuration, a quality of mixing for the testing steady state mixing configuration; and evaluate the trained machine learning model by comparing the mixing quality calculated for the testing steady state mixing configuration using the testing CFD model and the mixing quality predicted for the testing steady state mixing configuration using the trained machine learning model.

[0062] 20. The non-transitory computer readable storage medium of any of aspects 15-19, wherein the machine learning model is a deep learning model.

What is Claimed is:

1. A method, comprising:
generating, by one or more processors, a plurality of training computational fluid dynamic (CFD) models for a plurality of training steady state mixing configurations in which inlet streams are mixed in tanks, wherein each training CFD model is generated based on a plurality of steady state mixing factors associated with each training steady state mixing configuration;
calculating, by the one or more processors, a mixing quality for each training steady state mixing configuration using each respective training CFD model;
generating, by the one or more processors, a training dataset that includes the steady state mixing factors associated with each training steady state mixing configuration, and the calculated mixing quality for each training steady state mixing configuration;
and
training, by the one or more processors, a machine learning model, using the training dataset, to predict mixing qualities for steady state mixing configurations based on steady state mixing factors associated with the steady state mixing configurations.
2. The method of claim 1, further comprising:
applying, by the one or more processors, the trained machine learning model to new steady state mixing factors associated with a new steady state mixing configuration; and
predicting, by the one or more processors, based on applying the trained machine learning model to the steady state mixing factors associated with the new steady state mixing configuration, a mixing quality for the new steady state mixing configuration.
3. The method of claim 1, wherein the steady state mixing factors include one or more of: tank geometry, stirrer geometry, working volume, inlet configuration, outlet configuration, inlet flow rates for each inlet, outlet flow rates for each outlet, agitation speed, impeller speed, fluid Reynolds number for each substance, and other chemical and pharmaceutical properties for each substance.
4. The method of claim 1, wherein the mixing quality is a measure of standard deviation of trace concentration in the tank.
5. The method of claim 1, further comprising:
generating, by the one or more processors, a testing computational fluid dynamic (CFD) model for a testing steady state mixing configuration in which inlet streams are mixed in tanks, wherein the testing CFD model is generated based on a plurality of steady state mixing factors associated with the testing steady state mixing configuration;
calculating, by the one or more processors, a mixing quality for the testing steady state mixing configuration using the testing CFD model;
applying, by the one or more processors, the trained machine learning model to the steady state mixing factors associated with the testing steady state mixing configuration;

predicting, by the one or more processors, based on applying the trained machine learning model to the steady state mixing factors associated with the testing steady state mixing configuration, a quality of mixing for the testing steady state mixing configuration; and

evaluating, by the one or more processors, the trained machine learning model by comparing the mixing quality calculated for the testing steady state mixing configuration using the testing CFD model and the mixing quality predicted for the testing steady state mixing configuration using the trained machine learning model.

6. The method of claim 1, wherein the machine learning model is a deep learning model.

7. A computer system, comprising:

one or more processors; and

a non-transitory program memory communicatively coupled to the one or more processors and storing executable instructions that, when executed by the one or more processors, cause the processors to:

generate a plurality of training computational fluid dynamic (CFD) models for a plurality of training steady state mixing configurations in which inlet streams are mixed in tanks, wherein each training CFD model is generated based on a plurality of steady state mixing factors associated with each training steady state mixing configuration;

calculate a mixing quality for each training steady state mixing configuration using each respective training CFD model;

generate a training dataset that includes the steady state mixing factors associated with each training steady state mixing configuration, and the calculated mixing quality for each training steady state mixing configuration; and

train a machine learning model, using the training dataset, to predict mixing qualities for steady state mixing configurations based on based on steady state mixing factors associated with the steady state mixing configurations.

8. The computer system of claim 7, wherein a first set of one or more processors, of the one or more processors, generate the plurality of training computational fluid dynamic (CFD) models, and wherein a second set of one or more processors, of the one or more processors, train the machine learning model.

9. The computer system of claim 7, wherein the executable instructions, when executed by the one or more processors, further cause the processors to:

apply the trained machine learning model to new steady state mixing factors associated with a new steady state mixing configuration; and

predict, based on applying the trained machine learning model to the steady state mixing factors associated with the new steady state mixing configuration, a mixing quality for the new steady state mixing configuration.

10. The computer system of claim 9, wherein a third set of one or more processors, of the one or more processors, apply the trained machine learning model to the new steady state mixing factors associated with the new steady state mixing configuration and predict the mixing quality for the new steady state mixing configuration.

11. The computer system of claim 7, wherein the steady state mixing factors include one or more of: tank geometry, stirrer geometry, working volume, inlet configuration, outlet configuration, inlet flow rates for each inlet, outlet flow rates for each outlet, agitation speed, impeller speed, fluid Reynolds number for each substance, and other chemical and pharmaceutical properties for each substance.

12. The computer system of claim 7, wherein the mixing quality is a measure of standard deviation of trace concentration in the tank.

13. The computer system of claim 7, wherein the executable instructions, when executed by the one or more processors, further cause the processors to:

generate a testing computational fluid dynamic (CFD) model for a testing steady state mixing configuration in which inlet streams are mixed in tanks, wherein the testing CFD model is generated based on a plurality of steady state mixing factors associated with the testing steady state mixing configuration;

calculate a mixing quality for the testing steady state mixing configuration using the testing CFD model;

apply the trained machine learning model to the steady state mixing factors associated with the testing steady state mixing configuration;

predict, based on applying the trained machine learning model to the steady state mixing factors associated with the testing steady state mixing configuration, a quality of mixing for the testing steady state mixing configuration; and

evaluate the trained machine learning model by comparing the mixing quality calculated for the testing steady state mixing configuration using the testing CFD model and the mixing quality predicted for the testing steady state mixing configuration using the trained machine learning model.

14. The computer system of claim 7, wherein the machine learning model is a deep learning model.

15. A non-transitory computer readable storage medium storing computer-readable instructions that, when executed by one or more processors, cause the one or more processors to:

generate a plurality of training computational fluid dynamic (CFD) models for a plurality of training steady state mixing configurations in which inlet streams are mixed in tanks, wherein each training CFD model is generated based on a plurality of steady state mixing factors associated with each training steady state mixing configuration;

calculate a mixing quality for each training steady state mixing configuration using each respective training CFD model;

generate a training dataset that includes the steady state mixing factors associated with each training steady state mixing configuration, and the calculated mixing quality for each training steady state mixing configuration; and

train a machine learning model, using the training dataset, to predict mixing qualities for steady state mixing configurations based on based on steady state mixing factors associated with the steady state mixing configurations.

16. The non-transitory computer readable storage medium of claim 15, wherein the computer-readable instructions, when executed by the one or more processors, further cause the processors to:

apply the trained machine learning model to new steady state mixing factors associated with a new steady state mixing configuration; and

predict, based on applying the trained machine learning model to the steady state mixing factors associated with the new steady state mixing configuration, a mixing quality for the new steady state mixing configuration.

17. The non-transitory computer readable storage medium of claim 15, wherein the steady state mixing factors include one or more of: tank geometry, stirrer geometry, working volume, inlet configuration, outlet configuration, inlet flow rates for each inlet, outlet flow rates for each outlet, agitation speed, impeller speed, fluid Reynolds number for each substance, and other chemical and pharmaceutical properties for each substance.

18. The non-transitory computer readable storage medium of claim 15, wherein the mixing quality is a measure of standard deviation of trace concentration in the tank.

19. The non-transitory computer readable storage medium of claim 15, wherein the computer-readable instructions, when executed by the one or more processors, further cause the processors to:

generate a testing computational fluid dynamic (CFD) model for a testing steady state mixing configuration in which inlet streams are mixed in tanks, wherein the testing CFD model is generated based on a plurality of steady state mixing factors associated with the testing steady state mixing configuration;

calculate a mixing quality for the testing steady state mixing configuration using the testing CFD model;

apply the trained machine learning model to the steady state mixing factors associated with the testing steady state mixing configuration;

predict, based on applying the trained machine learning model to the steady state mixing factors associated with the testing steady state mixing configuration, a quality of mixing for the testing steady state mixing configuration; and

evaluate the trained machine learning model by comparing the mixing quality calculated for the testing steady state mixing configuration using the testing CFD model and the mixing quality predicted for the testing steady state mixing configuration using the trained machine learning model.

20. The non-transitory computer readable storage medium of claim 15, wherein the machine learning model is a deep learning model.