



# Mass transfer performance of CO<sub>2</sub> capture in rotating packed bed: Dimensionless modeling and intelligent prediction



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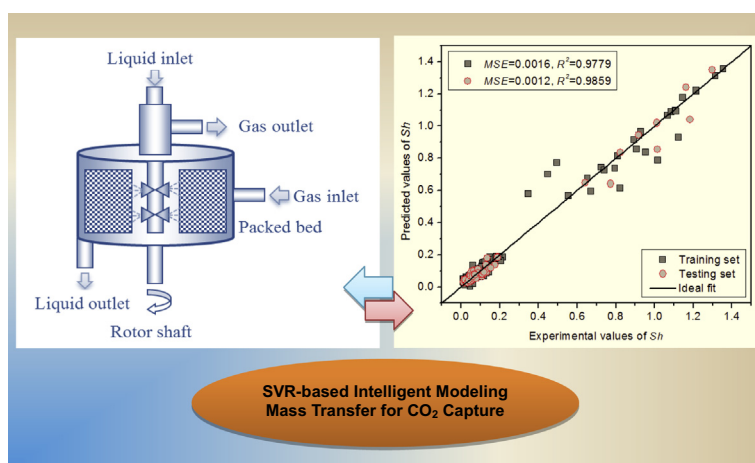
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## HIGHLIGHTS

- Intelligent modeling for mass transfer of CO<sub>2</sub> capture in rotating packed beds.
- Dimensional analysis was used to obtain the independent and dependent variables.
- Support vector regression (SVR)-based approach is developed for prediction.
- SVR is superior to multiple nonlinear regression and artificial neural network.

## GRAPHICAL ABSTRACT



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## ABSTRACT

Rotating packed beds have been demonstrated to be able to intensify the physicochemical process of multiphase transportation and reaction in the fields of energy and environment, and successfully applied in the field of CO<sub>2</sub> emission control. However, modeling and prediction of gas–liquid mass transfer especially for mass transfer with chemical reaction are rare due to the complexity of multiphase fluid flow and transportation. In view of the inaccuracy of semi-empirical models and the complexity of computational fluid dynamics models, an intelligent correlation model was developed in this work to predict the mass transfer coefficient more accurately for CO<sub>2</sub> capture with NaOH solution in different type rotating packed beds. This model used dimensional analysis to determine the independent variables affecting the mass transfer coefficients, and then used least squares support vector regression (LSSVR) for prediction. An optimized radial basis function was obtained as kernel function based on grid search coupled with simulated annealing (SA) and 10-fold cross-validation (CV) algorithms. The proposed model had the mean square error of 0.0016 for training set and 0.0012 for testing set. Compared with the models based on multiple nonlinear regression (MNR) and artificial neural network (ANN), the present model decreased mean squared error by 91.06% and 38.46% for training set and 94.57% and 53.85% for testing set respectively, suggesting it had superior performance on prediction accuracy and generalization ability.

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**Nomenclature**

$a$	gas–liquid interfacial area ( $\text{m}^{-1}$ )	$u_{Gf}$	superficial gas velocity ( $\text{m s}^{-1}$ )
$a_c$	centrifugal acceleration ( $\text{m}^2 \text{s}^{-1}$ )	$u_L$	actual liquid velocity ( $\text{m s}^{-1}$ )
$a_p$	surface area per unit volume of the bead ( $\text{m}^{-1}$ )	$u_{Lf}$	superficial liquid velocity ( $\text{m s}^{-1}$ )
$a_t$	surface area of the packing per unit volume of the bed ( $\text{m}^{-1}$ )	$V$	volume of 1 mol gas
$b$	bias term	$V_i$	volume inside the inner radius of the bed ( $\text{m}^3$ )
$c_L$	concentration of NaOH solution ( $\text{mol L}^{-1}$ )	$V_o$	volume between the outer radius of the bed and the stationary housing ( $\text{m}^3$ )
$c_G$	concentration of $\text{CO}_2$ in inlet gas ( $\text{mol L}^{-1}$ )	$V_t$	total volume of the RPB ( $\text{m}^3$ )
$D_G$	diffusion coefficient in the gas phase ( $\text{m}^2 \text{s}^{-1}$ )	$\mathbf{w}$	weigh vector
$D_L$	diffusion coefficient in the liquid phase ( $\text{m}^2 \text{s}^{-1}$ )	$X$	surface renewal parameter (m)
$d$	degree of the polynomial function	$\mathbf{x}$	input variable
$d_e$	hydraulic diameter (m)	$x_i$	$i$ th input variable
$d_p$	spherical equivalent diameter of the packing (m)	$x_{Ni}$	scaled value of the observed variable
$E^2$	mean squared error	$x_{\min}$	minimum observation value of the dataset
$e_i$	slack variable	$x_{\max}$	maximum observation value of the dataset
$G$	gas mass flux ( $\text{kg m}^{-2} \text{s}^{-1}$ )	$\Delta x$	spacing between plate corrugations (m)
$g$	acceleration due to gravity ( $\text{m s}^{-2}$ )	$\mathbf{y}$	output variable
$H$	Henry's law constant ( $(\text{mol/mol})/(\text{mol/mol})$ )	$y_i$	target output corresponding to the $i$ th input
$H'$	solubility coefficient ( $\text{kmol Pa}^{-1} \text{m}^{-3}$ )	$\hat{y}$	predicted value of $y$
$h$	axial height of the rotor (m)	$\bar{y}$	mean value of $y$
$\mathbf{I}$	an identity matrix	$z$	axial height of packing (m)
$K$	kernel function	<b>Greek letters</b>	
$K_{Ga}$	overall volumetric gas-side mass transfer coefficient ( $\text{s}^{-1}$ )	$\alpha_i$	$i$ th Lagrangian multiplier
$K_{La}$	overall volumetric liquid-side mass transfer coefficient ( $\text{s}^{-1}$ )	$\gamma$	regularization parameter
$k$	the number of sub-samples for cross-validation	$\varepsilon$	porosity of the packing or voidage ( $\text{m}^3/\text{m}^3$ )
$k_G$	local gas-side mass transfer coefficient ( $\text{kmol m}^{-3} \text{s}^{-1} \text{Pa}^{-1}$ )	$\mu_G$	dynamic viscosity of gas (Pa s)
$k_{Ga}$	local volumetric gas-side mass transfer coefficient ( $\text{s}^{-1}$ )	$\mu_L$	dynamic viscosity of liquid (Pa s)
$k_L$	local liquid-side mass transfer coefficient (m/s)	$\nu_G$	kinematic viscosity of gas ( $\text{m}^2 \text{s}^{-1}$ )
$k_{La}$	local volumetric liquid-side mass transfer coefficient ( $\text{s}^{-1}$ )	$\nu_L$	kinematic viscosity of liquid ( $\text{m}^2 \text{s}^{-1}$ )
$k_s$	a constant obtained from experimental results ( $\text{mol}^2 \text{s m}^{-8} \text{Pa}^{-2}$ )	$\rho_G$	density of gas ( $\text{kg m}^{-3}$ )
$L$	liquid mass flux ( $\text{kg m}^{-2} \text{s}^{-1}$ )	$\rho_L$	density of liquid ( $\text{kg m}^{-3}$ )
$l$	characteristic length (m)	$\sigma$	surface tension ( $\text{kg s}^{-2}$ )
$N$	number of samples	$\sigma_c$	critical surface tension of packing ( $\text{kg s}^{-2}$ )
$N_H$	neuron number in hidden layer	$\sigma_w$	surface tension of water ( $\text{kg s}^{-2}$ )
$N_p$	the number of input variables	$\sigma^2$	squared bandwidth of RBF kernel
$P$	operating pressure (Pa)	$\varphi$	mapping function
$\Delta P$	pressure drop (Pa)	$\psi$	sphericity of packing
$Q_G$	gas flow rate ( $\text{m}^3 \text{s}^{-1}$ )	$\Omega_{ij}$	scalar product between a pair of input points
$Q_L$	liquid flow rate ( $\text{m}^3 \text{s}^{-1}$ )	$\omega$	rotational speed ( $\text{rad s}^{-1}$ )
$\mathbf{R}$	space of the output features $y_i$	$\eta$	$\text{CO}_2$ capture efficiency (%)
$\mathbf{R}^d$	space of the input features $x_i$	<b>Dimensionless groups</b>	
$R^2$	coefficient of determination (COD)	$Gr_G$	Grashof number of the gas phase ( $l^3 a_c / \nu_G^2$ )
$r_h$	hydraulic radius of the packings, $\varepsilon/a_t$ , (m)	$Gr_L$	Grashof number of the liquid phase ( $l^3 a_c / \nu_L^2$ )
$r_i$	inner radius of the packed bed (m)	$Mr$	liquid–gas molar ratio ( $(Q_L c_L)/(Q_G c_G)$ )
$r_o$	outer radius of the packed bed (m)	$Re_G$	Reynolds number of the gas phase ( $d_e u_G / \nu_G$ or $G/a_t \nu_G$ )
$r_{avg}$	average radius of packings, $(r_h + r_o)/2$ (m)	$Re_L$	Reynolds number of the liquid phase ( $d_e u_L / \nu_L$ or $L/a_t \nu_L$ )
$T$	operating temperature (K)	$Re_\omega$	rotational Reynolds number ( $\omega r_{avg}^2 / \nu_G$ )
$t$	a constant in polynomial kernel function	$Sc_G$	Schmidt number of the gas phase ( $\nu_G / D_G$ )
$u_G$	actual gas velocity ( $\text{m s}^{-1}$ )	$Sc_L$	Schmidt number of the liquid phase ( $\nu_L / D_L$ )
		$Sh$	Sherwood number ( $K_G a / (D_G a_t^2)$ )
		$We_L$	Weber number of the liquid phase ( $L^2 / \rho_L a_t \sigma$ )

**1. Introduction**

It has been demonstrated that carbon dioxide ( $\text{CO}_2$ ) as a greenhouse gas from human activity especially from combustion of fossil fuel is responsible for the global warming and the greenhouse effect [1,2]. Anthropogenic  $\text{CO}_2$  emissions control and reduction have become an important scientific, environmental and even international economic and political issue.

Currently, post-combustion  $\text{CO}_2$  capture can be roughly categorized as chemical absorption, physicochemical adsorption, membrane, cryogenics, chemical looping combustion (CLC) and biological sequestration according to their scientific principles [3,4]. Among these approaches, chemical absorption is comprehensively considered as a good choice for its advantages of high efficiency, low cost and mature technology [3]. Over last decades, conventional gas–liquid contactors such as packed tower, spray

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