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Fuzzy Model of Smart Toilet Bowl-Bidet System

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Abstract. This paper proposes an application of a Takagi-Sugeno fuzzy model to the prediction of complex mass transfer behavior in smart toilet bidet systems. The model is constructed through the integration of fuzzy logic theory, nonlinear autoregressive moving average exogenous input models, neural networks, and data clustering algorithms. To develop the model for estimating the air quality of the smart toilet-bidet system, many datasets are collected from a smart toilet bidet model equipped with an automatic odor/bacteria suction system using Sulfur hexafluoride (SF_6) gas. Many case studies were carried out as a function of the suction flow rate, suction angle, the number of suction holes, and suction hole size. The inputs for training the fuzzy model are the size, number, and angles of suction holes, whereas its output is the undesirable gas concentration. The trained fuzzy model is tested using different datasets. Modeling and testing results show the effectiveness of the fuzzy model in predicting the gas concentration of the toilet bowl. The proposed fuzzy model is expected to be useful in the implementation of smart toilet bowl systems in the near future.

AMS Subject Classification 2020: 03E75; 58D30
Keywords and Phrases: Fuzzy logic, Toilet seat, Bidet, Indoor air quality.

1 Introduction

The indoor air quality has been reported to be several times worse than that of outdoor air ([1], [4]). Several factors such as dust, tobacco smoke, and microorganisms contribute to poor indoor air quality; In particular, microorganisms can proliferate in high relative humidity indoors or emerge from feces in toilets Studies by several researchers ([6], [16], [7], [11]) have shown that many countries have legislated a minimum requirement for indoor air quality. For instance, in Singapore, the regulated value for bacteria is lower than 500 CFU/m^3.

Numerous studies have been conducted to find a means to eliminate unwanted odor and bacteria from bathrooms. In particular, most methodologies have been related to designing a more effective ventilation system. Chung et al.[5] conducted numerical simulations on the airflow and contaminant particles in the bathroom by using floor exhaust ventilation. Tung et al.[14] used a mock bathroom to verify the concentration of tracer gas at several points in a typical ceiling ventilation system. Their results indicated that the odor removal efficiency improved with an increase in the flow rate for ventilation and a reduction in the distance between the toilet and the exhaust vent. Best et al.[3] conducted a study on toilet lids, in which they measured aerosolized bacteria from a contaminated toilet. In their study, it was found that the bacteria could rise up to 25 cm above the toilet seat, which would cause contamination of the entire bathroom (Figure 1).

However, the condition of contamination improves rapidly with the closing of the toilet bowl lid. Nevertheless, intractable problems apparently occur when the toilet bowl lid is opened and closed. Bacteria keep rising continuously and contaminating the bathroom (Figure 2).

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Figure 1: Ejection of toilet bacteria via flushing of toilet bowl

Figure 2: Contamination of infectious bacteria in a bathroom

In addition, users must unfortunately continue to suffer from the smell of unpleasant odors. Hence, Seo and Park[10] proposed the application of an odor/bacteria suction system to a toilet bowl to prevent unwanted elements such as odor and bacteria from emerging out of toilets. They verified through numerical studies that when the system is used in a toilet seat, it is effective in removing odors and bacteria from feces.

However, further research needs to be directed at developing real-time odor/bacteria forecasting algorithms so as to effectively implement robust automatic control systems to the smart toilet bowl system. The forecasting of odor/bacteria in toilet bowls is a highly complex issue that has not yet been definitely resolved, owing to the highly nonlinear and uncertain nature of the concerned environment. With this in mind, in the present study, an intelligent model is proposed for predicting the complex behavior of the smart toilet bowl system. The model is developed through the integration of nonlinear autoregressive moving average exogenous input models, the TakagiSugeno fuzzy model, the backpropagation algorithm, and the partition grid algorithm. Surprisingly, an effective fuzzy model for toilet bowls equipped with bidet systems has not yet been developed conceptually or thoroughly evaluated empirically. This work would fill some of these gaps in the literature and provides an alternative design framework for modeling a smart toilet bowl-bidet system. To develop the model for estimating the air quality of the smart toilet-bidet system, many datasets are collected from a smart toilet bidet system using Sulfur hexafluoride (SF_6) gas. Many case studies were carried out as a function of the suction flow rate, suction angle, the number of suction holes, and suction hole size. The results showed that the model effectively predicts the air flow and tracer gas concentration around the toilet.

The rest of this paper is organized as follows. Section 2 introduces the proposed fuzzy model. Section 3 describes the experimental protocol. Section 4 discusses the modeling process and its results. Section 5 presents the concluding remarks.

2 Proposed fuzzy model

The numerical model used in this study for modeling the behavior of the smart toilet bowl-bidet system is a modified TakagiSugeno fuzzy model. The antecedent parameters of the TakagiSugeno fuzzy model are optimized using the backpropagation learning algorithm, and the consequent parameters are determined via the weighted least-squares estimator.

2.1 Autoregressive moving average exogenous fuzzy model

In 1985, Takagi and Sugeno proposed a fuzzy model that is described as fuzzy IF-THEN rules such that a nonlinear system can be represented by local linear input-output relations ([12]). The local dynamics of the fuzzy inference system proposed in this study takes the form of

$$\begin{aligned} &R_j : \ \textbf{IF} \ u_1 \ is \ p_1 \ and \ u_2 \ is \ p_2 \ and \ ... \ and \ u_i \ is \ p_i \\ &\textbf{THEN} \ \hat{\mathbf{y}}^j(k) = \sum_{i=1}^{n_1} \mathbf{a}_i^j \mathbf{y}(k-i) + \sum_{i=1}^{n_2} \mathbf{b}_i^j \mathbf{u}(k-i-n_4) + \sum_{i=1}^{n_3} \mathbf{c}_i^j \boldsymbol{\epsilon}(k-i-n_5). \end{aligned} \tag{1}$$

where R_j is the j^{th} rule; u_i is the i^{th} premise variable; p_i^j is the associated parameter; k is the integer value; and n_1, n_2, and n_3 are the number of delay steps in the output, input, and the disturbance terms, respectively. n_3 and n_4 are the discrete dead-times, and $\mathbf{a}_i$, $\mathbf{b}_i$, and $\mathbf{c}_i$ are the coefficient matrices to be estimated. The output $\mathbf{y}(k)$, input $\mathbf{u}(k)$, and the associated scheduling vector are expressed in Eqs. (2)-(5).

$$\mathbf{u} \in \{y(k-1), ..., y(k-n_1), u(k-1), ...u(k-n_2-n_3), ..., \epsilon(k-1), ...\epsilon(k-n_4-n_5)\} \tag{2}$$

The linear j^{th} fuzzy model at the operating point $\mathbf{u}$ can be integrated into a linear time-varying dynamic model as

$$\begin{gathered}\hat{\mathbf{y}}(k)=\sum_{i=1}^{n_1}\sum_{j=1}^{N_r}\frac{\prod_{i=1}^{n_o}\boldsymbol{\omega}_i^j(u_i)}{\sum_{j=1}^{N_r}\prod_{i=1}^{n_o}\boldsymbol{\omega}_i^j(u_i)}\mathbf{a}_i^j\mathbf{y}(k-i)+\\ \sum_{i=1}^{n_2}\sum_{j=1}^{N_r}\frac{\prod_{i=1}^{n_o}\boldsymbol{\omega}_i^j(u_i)}{\sum_{j=1}^{N_r}\prod_{i=1}^{n_o}\boldsymbol{\omega}_i^j(u_i)}\mathbf{b}_i^j\mathbf{u}(k-i-n_4)+\\ \sum_{i=1}^{n_3}\sum_{j=1}^{N_r}\frac{\prod_{i=1}^{n_o}\boldsymbol{\omega}_i^j(u_i)}{\sum_{j=1}^{N_r}\prod_{i=1}^{n_o}\boldsymbol{\omega}_i^j(u_i)}\mathbf{c}_i^j\boldsymbol{\epsilon}(k-i-n_5)\end{gathered}\tag{3}$$

where $\boldsymbol{\omega}_i^j(u_i)$ is the membership function (MF) of u_i, and N_r is the number of local linear models. In this study, the parameters of the MF are optimized using the backpropagation algorithm, whereas $\mathbf{a}_i$, $\mathbf{b}_i$, $\mathbf{c}_i$ and are estimated via the weighted least-squares estimator.

2.2 Parameter optimization

To determine the antecedent parameters of the proposed model, the model can be formulated as a minimum error problem such that

$$Minimize\ \mathbf{e}=\frac{1}{2}\{\hat{\mathbf{y}}(k)-\tilde{\mathbf{y}}(k)\}^2\tag{4}$$

The problem becomes optimization of the parameters of the MF $\omega_i^j(u_i)$ such that $\mathbf{e}$ is minimized using the learning algorithms:

$$\begin{aligned}m_i^j(k)&=m_i^j(k-1)-\eta_1\frac{\partial(k)}{\partial(\omega_i^j)}|\omega_i^j\\ &=m_i^j(k-1)-2\eta_1\frac{\prod_{i=1}^{n_o}\omega_i^j(u_i(k-1))(\hat{y}(k-1)-\tilde{y}(k-1))}{\sum_{j=1}^{N_r}\prod_{i=1}^{n_o}\omega_i^j(u_i(k-1))}\frac{u_i(k-1)-m_i^j(k-1)}{\sigma_i^j(k-1)}^2\end{aligned}\tag{5}$$

for the mean values and

$$\begin{aligned}\sigma_i^j(k)&=\sigma_i^j(k-1)-\eta_2\frac{\partial(e(k))}{\partial(\omega_i^j)}|\sigma_i^j=\sigma_i^j(k-1)\\ &=\sigma_i^j(k-1)-2\eta_2\frac{\prod_{i=1}^{n_o}\omega_i^j(u_i(k-1))(\hat{y}(k-1)-\tilde{y}(k-1))}{\sum_{j=1}^{N_r}\prod_{i=1}^{n_o}\omega_i^j(u_i(k-1))}\frac{(\hat{y}^j(k-1)-\hat{y}(k-1))(u_i(k-1)-m_i^j(k-1))^2}{(\sigma_i^j(k-1))^3}\end{aligned}\tag{6}$$

for the standard deviations, where η_1 and η_2 are the learning-rate parameters. When the parameters of the fuzzy antecedent part are determined, the final output of the fuzzy model is expressed as a linear combination of the polynomial parameters. Hence, the consequent parameters can be identified using the least-squares method

$$\boldsymbol{\theta}_j=(\mathbf{H}(k)^T\boldsymbol{\omega}_j\mathbf{H}(k))^{-1}\mathbf{H}(k)^T\boldsymbol{\omega}_j\tilde{\mathbf{y}}(k),\tag{7}$$

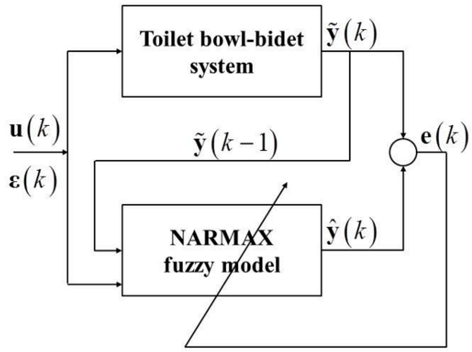

Figure 3: Configuration of proposed algorithm

where

$$\begin{aligned}\mathbf{H}(k) = [&\mathbf{y}(k-1)^T, ..., \mathbf{y}(k-n_1)^T, ...\\ &\mathbf{u}(k-1)^T, ..., \mathbf{u}(k-n_2-n_3)^T, ...\\ &\boldsymbol{\epsilon}(k-1)^T, ...\boldsymbol{\epsilon}(k-n_4-n_5)^T]\end{aligned} \tag{8}$$

$$\boldsymbol{\theta}_j = [\mathbf{a}_{1,j}, ..., \mathbf{a}_{n,j}, \mathbf{b}_{1,j}, ..., \mathbf{b}_{m,j}, \mathbf{c}_{1,j}, ..., \mathbf{c}_{l,j}]. \tag{9}$$

Here, $\tilde{\mathbf{y}}(k)$ denotes the measured data, and ω_j is the weighting factor. Figure 3 shows the basic configuration in which the proposed system is implemented.

2.3 Proposed algorithm

The proposed algorithm is implemented in the following steps (as shown in Figure 4).

Step 1: Air quality data are collected from the laboratory.

Step 2: The digital signal processing technique is applied to the selected dataset of input-output signals in order to filter out noisy signals that are undesirable data.

Step 3: Based on the processed signals, the grid partition clustering algorithm is applied and the results are used as the initial values of the premise part of the TakagiSugeno fuzzy model.

Step 4: Once the antecedent MFs are initialized using the grid partition clustering algorithm, the mean and standard deviation values of the MFs are optimized using the backpropagation algorithm.

Step 5: Once the values of the premise parameters are fixed, the consequent parameters are optimized using the weighted least-squares algorithm.

Step 6: The performance of the fuzzy model is estimated via various evaluation indices: percent error in peak, bias, mean square error, root mean square error (RMS), and coefficient of determination. If the prediction performance is not satisfactory (i.e., the errors are larger than the allowable error limits), the modeling procedure goes back to Step 4. Note that Step 4 to Step 6 are repeated until the errors converge to desirable values. For example, the number of MFs can be adjusted. The target errors are determined by users.

Step 7: When the model estimates comply with the specified boundaries of errors, the model is tested using other datasets that are not used for the training process. In this study, the specified boundaries of errors are determined qualitatively by visual inspection of the time series as well as quantitatively by means of an evaluation index such as R^2. If the prediction is not satisfactory, the procedure goes back to Step 3. If it is satisfactory, the algorithm stops.

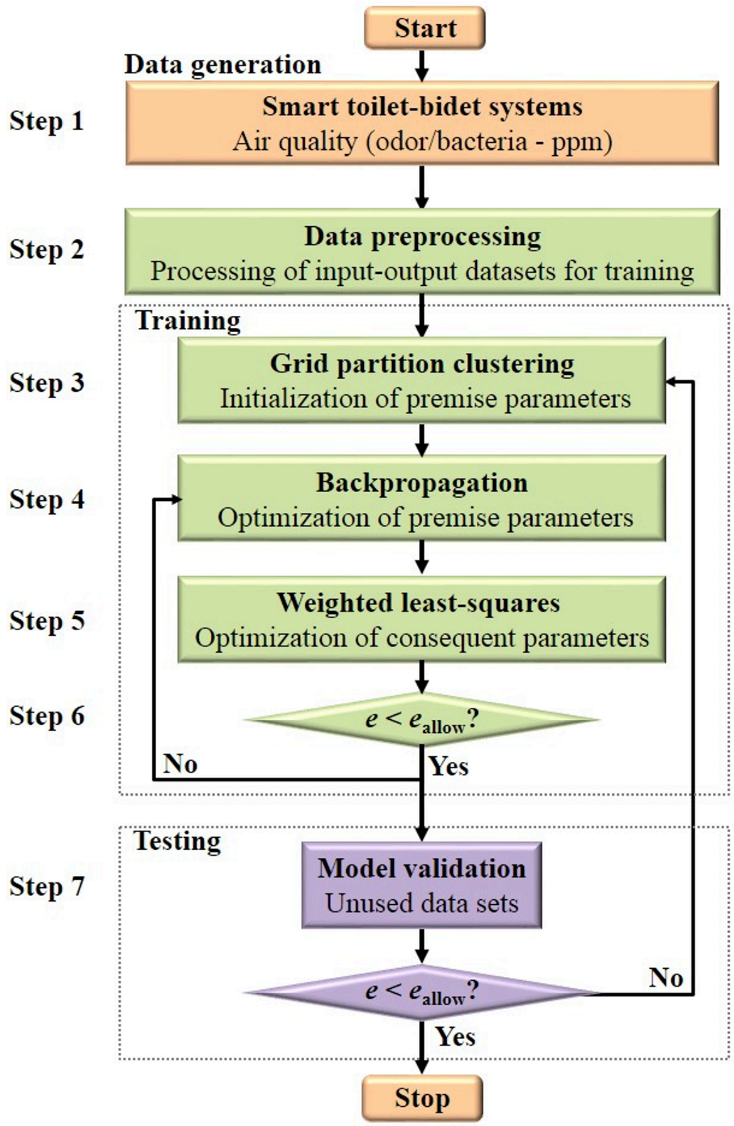

Figure 4: Flowchart of parameter optimization by proposed model

Figure 5: Experimental chamber

It should be noted that trial and error is required for Step 4 to Step 7 [9]. When it is difficult to develop an effective model between Step 4 and Step 7, returning to Step 2 and/or Step 3 is recommended. Based on various combinations of the input-output signals, it is sometimes possible to improve the modeling performance. It should also be noted that the computational costs of calculating the output increase significantly when the number of input variables increases, thereby making a high-dimensional fuzzy model unfeasible. However, it will also make it difficult to develop an effective controller, based on the identified model ([13], [15]). It is often counterproductive to consider a high number of input variables in the prediction model for a restricted purpose ([8]). Hence, it is desirable to carefully conduct the correlation analysis for the input-output signal datasets.

3 Experimental study

A new suction system, which was installed at the bottom of the toilet seat, was tested to evaluate its performance. Figure 5 shows a $5m^3$ chamber equipped with a ventilation system. Figure 6 shows the suction toilet system in the chamber. The ventilation system in the chamber serves the purpose of ensuring appropriate control of the level of the background gas. A schematic of the experimental setup is shown in Figure 7.

As shown in Figure 8, an experimental toilet seat with a suction system was placed on a toilet bowl. At the initial stage, 20 equidistant suction holes were created, and the sizes of the holes (hereafter referred to as suction tips) were 33, 44, 55, 66, 77, and 88 mm^2. Each suction tip size was tested separately by replacing them. Suction was achieved via a vacuum pump (DOA-P704-AC, GAST Manufacturing, Inc., Benton Harbor, MI), and the air flow rates were in the range of 420 LPM. SF_6 was used as the trace gas, and its flow rate was 1 LPM; it was released at the bottom of the toilet. To ensure uniform spreading of the gas, foam blocks were placed in the toilet bowl as the gas was released out of a tube with an inner diameter of 2 mm.

The sampling point of the gas was the center of the toilet seat, and its elevation was the same as that

Figure 6: Toilet bowl-bidet system in environmental chamber

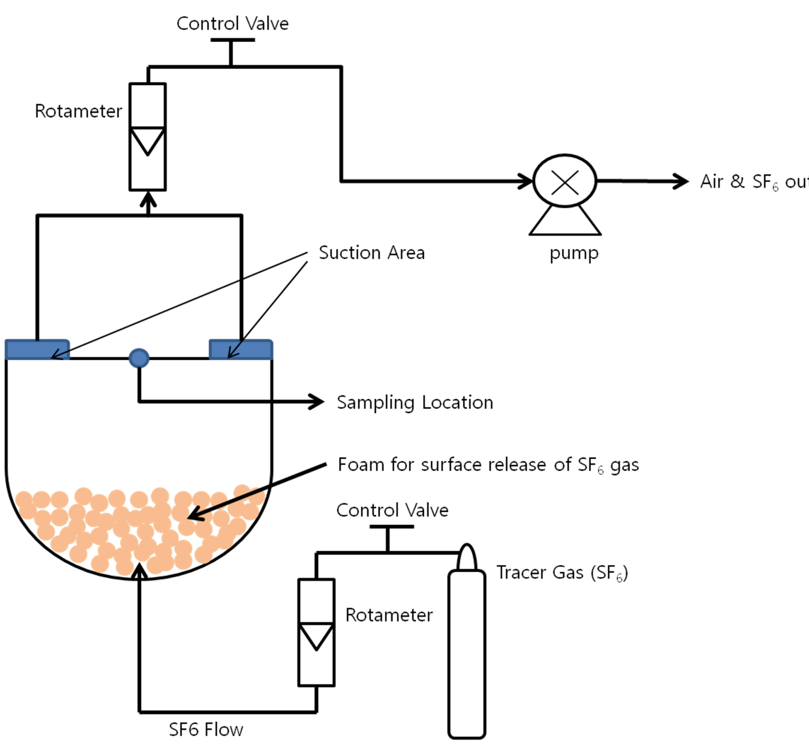

Figure 7: Schematic of experimental setup

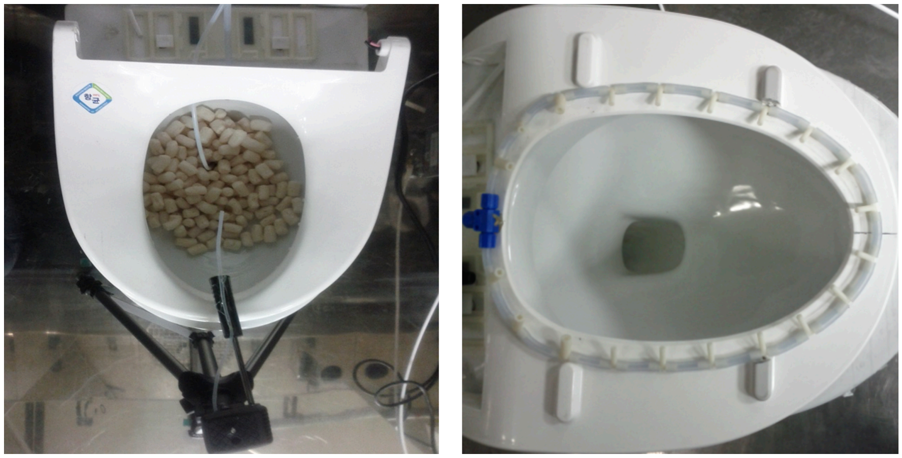

Figure 8: Suction system at bottom of toilet seat

of the seat. A photoacoustic gas analyzer (model 1312, CAI Inc., Orange, CA) was used to determine the concentration of the gas.

4 Simulation results

4.1 Parameter setting

Details of the selected experimental case studies are presented in Table 1. The evaluation was performed in the order of the suction tip angle, suction tip size, number of suction tips, and flow rate. It should be noted that a suction tip angle of 90 refers to the suction surface facing the bottom.

The gas concentration at the release point of the tracer was set as approximately 660 ppm. The input and output signals for training are shown in Figure 9.

4.2 Performance evaluation

Bennett et al. [2] outlined various methods for assessing the performance of environmental models, including both conventional and innovative approaches, in a systematic way.

4.2.1 Visual performance analysis

The performance of the fuzzy models can be judged by visual inspection (i.e., viewing patterns in data). It is easy to detect under-modeled or unmodeled patterns and capture the overall behavior of the model without performing extensive quantitative analysis. In many problems, a simple visual inspection of the models is sufficient [2].

Figure 10 and Figure 11 show the prediction of the model; specifically, the training and the testing results are shown in Figure 10 and Figure 11, respectively. In both figures, the dotted lines represent the experimental data points whereas the solid red lines indicate the predicted values. As is seen from the figures, there is a strong agreement between the data and the model predictions; in other words, the fuzzy model is highly effective in predicting the behavior of the smart toilet bowl-bidet system. Figure 12 and Figure 13 show the residual error plots for the proposed model. The residual errors of the model appear randomly; i.e., no systematic errors are found in the models. For instance, a high density of positive/negative values is not found in the plots, which indicates that the model does not tend to overestimate or underestimate the measured values [2].

Table 1: Experimental cases

Case	Suction Tip Size(mm)	# of Suction Tips	Suction Tip Angle (o)	Suction Flow Rate(LPM)
1	4 by 4	2	90	16
2	4 by 4	2	45	16
3	3 by 3	2	90	16
4	5 by 5	2	90	16
5	6 by 6	2	90	16
6	7 by 7	2	90	16
7	8 by 8	2	90	16
8	4 by 4	4	90	16
9	4 by 4	6	90	16
10	4 by 4	4	90	4
11	4 by 4	4	90	8
12	4 by 4	4	90	12
13	4 by 4	4	90	20

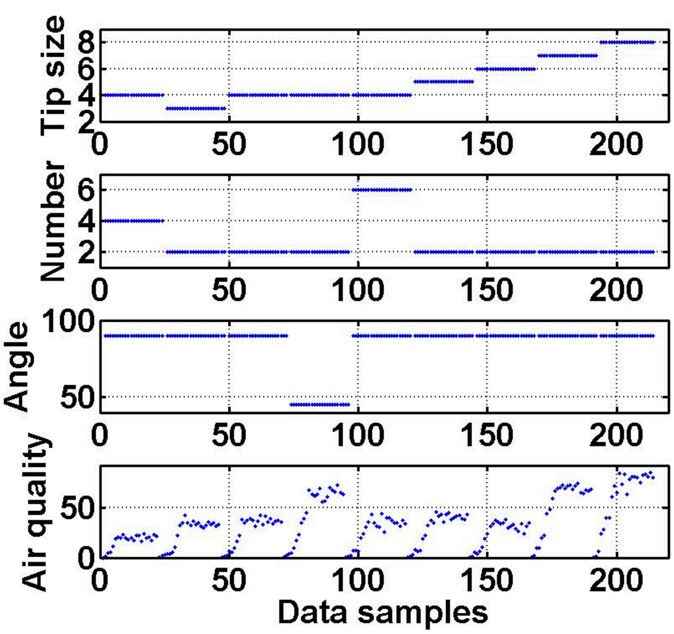

Figure 9: Set of input and output signals for training

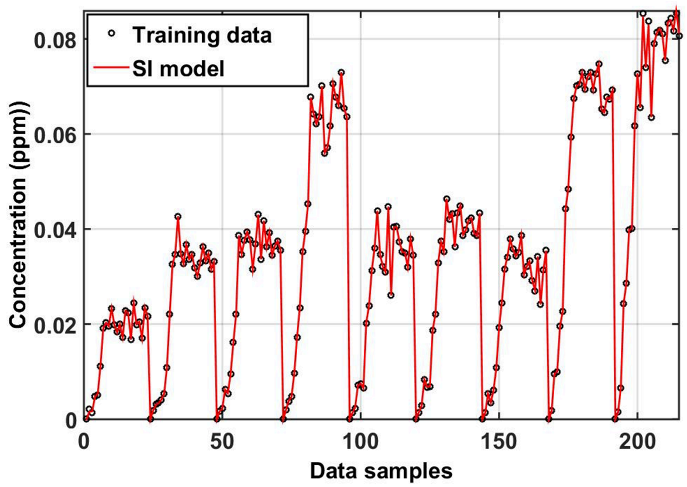

Figure 10: Prediction performance: training results

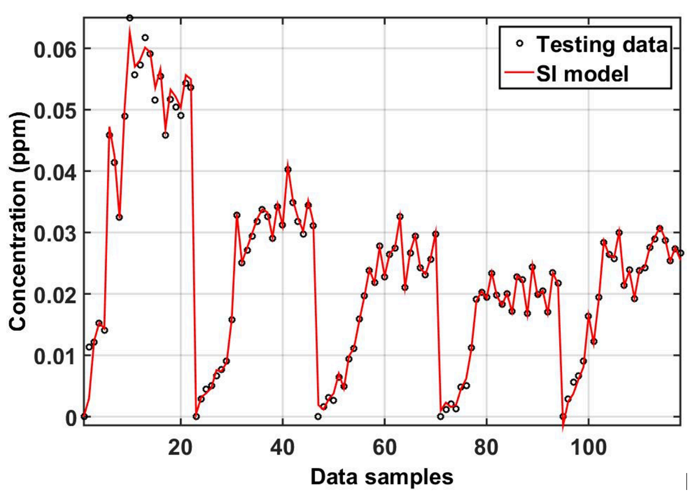

Figure 11: Prediction performance: validation results

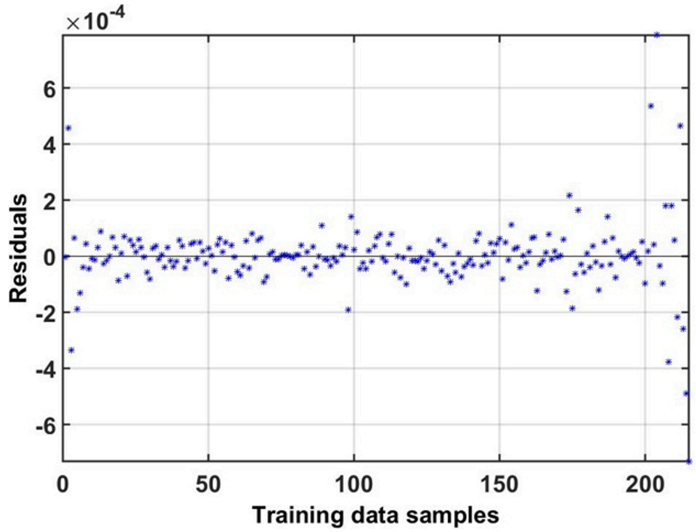

Figure 12: Residual plot: training

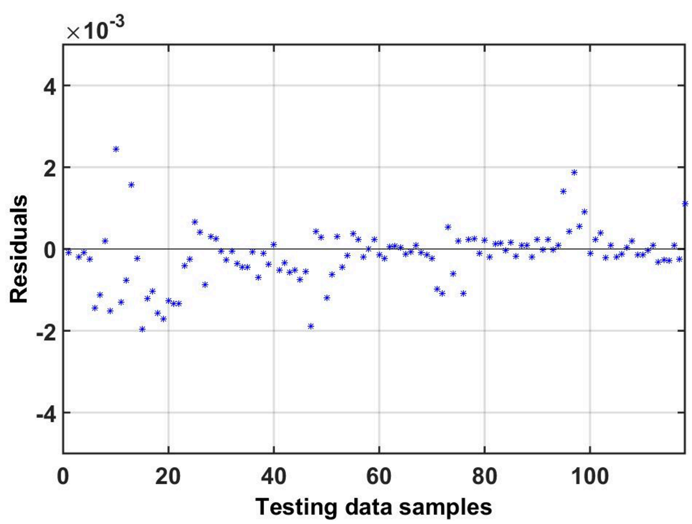

Figure 13: Residual plot: validation

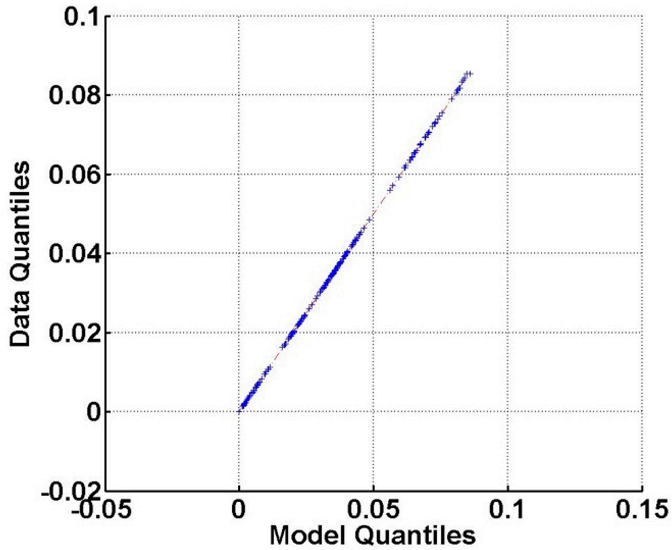

Figure 14: QQ plot: training

Figure 14 and Figure 15 show the quantile-quantile (QQ) plots of the fuzzy models and measured data. If the model and data have the same distribution, the QQ plot will be linear [2]. From Figure 14 and Figure 15, it is seen that all the QQ plots are closely linear, which means that both the models and the datasets originate from the same distribution, as shown in Figure 16 and Figure 17.

4.2.2 Quantitative analysis

In order to quantify the modeling error, several evaluation indices were used, as presented in Table 2. In Table 2,$\hat{y}$ is the forecasting value, $\tilde{y}$ denotes the data measured in the laboratory, and is the number of data points. As the first evaluation index, the percent error in peak (J_1) was used to determine whether the fuzzy models could generate a data range similar to observed data. As the second and third evaluation indices, the bias (J_2, the mean of the residuals) and the mean square error (J_3) were adopted to determine whether the fuzzy models tend to overestimate and underestimate the measured data, respectively. The RMSE (J_4) was also calculated to express the error metric in the unit of mg/m^2. To determine how well the fuzzy models capture the variance in the measured data, the coefficient of determination (J_5) was also used as an evaluation index [2].

As shown in Table 2, the proposed fuzzy model is effective in forecasting the complex behavior of air quality variations. According to all the indices, the proposed model demonstrates superior performance. The index J_1 in the proposed model is negative because the fuzzy model overestimates the overall data values slightly. In all the cases, the level of validation error is higher than the level of training error, as indicated by all the indices. However, the occurrence of both positive and negative errors in J_2 could result in a value close to zero, and thus, indices J_3 and J_4 account for this issue. The RMSE provides a metric in the unit of ppm/m^2, yielding values between 0.207 ppm/m^2 and 1.246 ppm/m^2, for all the training and testing models subject to clean data. Until the noise level of 5 percent,the coefficients of determination (J_5) for the proposed fuzzy model range from 0.956 to 1, indicating a strong agreement between the model and data. It should be noted that the coefficients of determination of the fuzzy model are 1 for the training data and 0.993 for the testing data. The coefficients of determination of the fuzzy model under random noises range from 0.623 to 0.980. Results of simulation using noise-contaminated data show that the proposed fuzzy model has a fairly robust performance against the measurement noises; however, the model performance degrades when

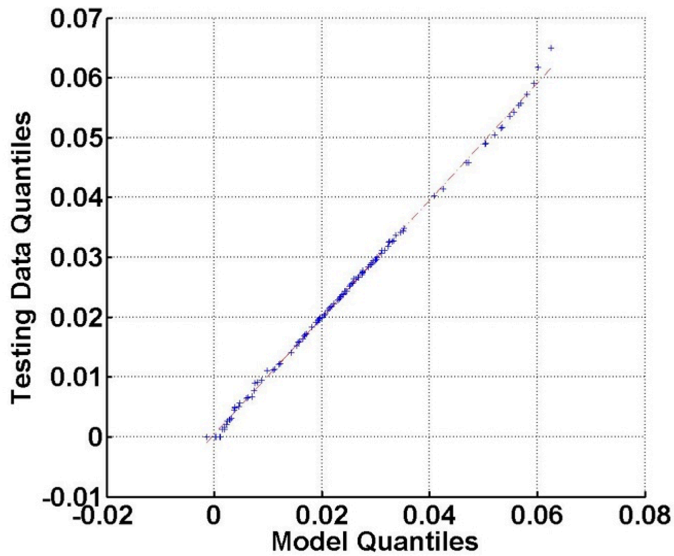

Figure 15: QQ plot: validation

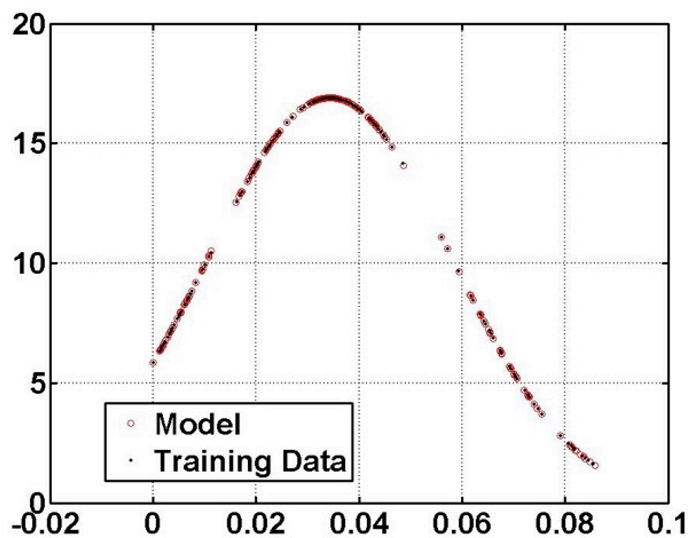

Figure 16: Data distribution: training

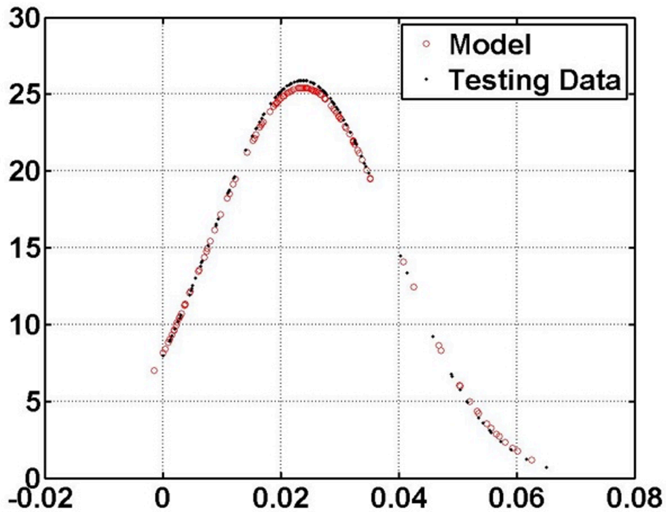

Figure 17: Data distribution: validation

Table 2: Performance evaluation of proposed fuzzy model

Index	Equation	Training	Testing Clean data	Noise 1%	Noise 5%	Noise 10%	Noise 20%
J_1	$\frac{max(\tilde{y}_i)-max(\hat{y}_i)}{max(\tilde{y}_i)} * 100$	-0.514	-10.207	1.584	-4.740	-69.061	-12.216
J_2	$\frac{1}{N_t}\sum_{i=1}^{N_t}(\tilde{y}-\hat{y})$	1.524e-6	-0.226	0.536	-0.151	1.338	1.211
J_3	$\frac{1}{N_t}\sum_{i=1}^{N_t}(\tilde{y}-\hat{y})^2$	0.043	1.553	4.677	10.36	38.223	88.743
J_4	$\sqrt{\frac{1}{N_t}\sum_{i=1}^{N_t}(\tilde{y}-\hat{y})^2}$	0.207	1.246	2.162	3.219	6.182	9.420
J_5	$1-\frac{\frac{1}{N_t}\sum_{i=1}^{N_t}(\tilde{y}-\hat{y})^2}{\frac{1}{N_t}\sum_{i=1}^{N_t}(\bar{y}-\hat{y})^2}$	1	0.993	0.980	0.956	0.838	0.623

contaminated data are directly used up to a noise level of 20 percent without filtering the undesirable features from the raw data.

5 Conclusion

In this paper, a novel fuzzy model was proposed for predicting the complex behavior of a bathroom toilet bowl equipped with a smart bidet system. To develop the proposed model, numerous datasets were collected from a smart toilet bowl-bidet system in an environment-controlled chamber. The size, number, and angles of the suction tip were considered as the input variables, whereas the tracer gas concentration was used as the output data. It was demonstrated through extensive testing that the proposed fuzzy model is effective in modeling the migration of the gas concentration. The proposed prediction model is expected to be useful for the implementation of a real-time control system for optimal smart bidet systems.

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