Optimization of Sensor Locations for Measurement of Flue Gas Flow in Industrial Ducts and Stacks Using Neural Networks

Haizhuang Kang, Qingping Yang, *Member, IEEE*, Clive Butler, Tuqiang Xie, and Fabrizio Benati

***Abstract*—This paper presents a novel application of neural network modeling in the optimization of sensor locations for the measurement of flue gas flow in industrial ducts and stacks. The proposed neural network model has been validated with an experiment based upon a case-study power plant. The results have shown that the optimized sensor location can be easily determined with this model. The industry can directly benefit from the improvement of measurement accuracy of the flue gas flow in the optimized sensor location and the reduction of manual measurement operation with Pitot tube.**

***Index Terms*—Data acquisition, fluid flow measurement, neural networks, optimization, sensor location.**

I. Introduction

CURRENT measurements of emissions of pollutants to the environment have errors in excess of 20% at most thermal power stations and other industrial installations [1]. This is mainly due to the nonoptimum sensor location, inaccuracies in the measurement of flue gas flows, and the fact that the gas samples collected do not accurately represent the entire sample. In order to reduce the measurement error, it is necessary to optimize sensor locations in industrial ducts and stacks. The measurement accuracy is significantly influenced by the gas samples that do not accurately represent the entire sample. In practice, this is largely due to the unstable gas flow in the sampled locations. A neural network model [2] was successfully set up to establish the relationship between the gas flows in a sampling location and a reference one which is stable and representative. In this paper, a novel neural network model is presented to optimize sensor location. It is the inverse model of the [2], which can predict the velocity profiles in ducts and stacks with flowrate and sensor location. Then it can optimize the sensor location according to velocity profiles on each section with the criterion of ISO 10780 [3].

Because setting up relationships between velocity, flowrate and sensor location is a multi-input, nonlinear problem, it is difficult to model using a conventional mathematical method. The use of artificial neural networks is proposed due to its learning ability, and capacity for solving nonlinear and complicated problems, among other advantages [4]. The significance of this neural network model is that it can provide an effective way to calculate velocity profiles on each section in ducts and stacks over the traditional method CFD. With the proposed neural network model, the optimized sensor location can be quickly found. The flue gas flow can be more accurately measured at the optimized sensor location.

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II. Modelling of the Flue Gas Flow

A. Measurement Method of the Flue Gas Flow Rate

The measurement of the flue gas flow rate was performed manually using a traditional method with a Pitot tube according to the ISO 10780. The average velocity of the gas stream is calculated from the individual velocity measurements using a Pitot tube to transverse the cross-section of a duct or stack. The volume flow rate q_v is determined as the product of the cross-sectional area and the average velocity of the gas stream at that cross-section.

The average Pitot tube pressure difference $\Delta\overline{p}$ is calculated according to the ISO 10780

$$\Delta\overline{p} = \frac{1}{n^2}\left(\sum_{i=1}^{n} \sqrt{\Delta p_i}\right)$$

where Δp_i is the pressure difference at sampling point I, in kilopascals. n is the number of sampling points.

The average gas velocity $\overline{v}$ is then given as [2]

$$\overline{v} = KC\sqrt{\frac{T_s \Delta\overline{p}}{p_e M_s}}$$

where

- K Pitot tube coefficient;
- C Pitot tube constant = 129 (m/s) $*$ [kg/(kmol $*$ K)]$^{1/2}$;
- T_s average temperature at the section, in Kelvins;
- $\Delta\overline{p}$ average Pitot tube pressure difference in the section, in kilopascals;
- p_e absolute gas pressure, in kilopascals;
- M_s molar mass of gas.

Thus, the volume flow rate at the duct condition is

$$q_{vs} = \overline{v} * A$$

where

- $\overline{v}$ average gas velocity in one section, in m/s;
- A cross-sectional area, in m^2;
- q_{vs} volume flow rate at duct condition, in m^3/s.

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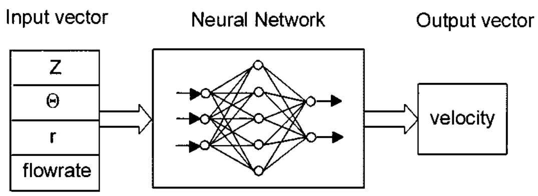

Fig. 1. Neural network model for predicting the individual velocity with flowrate.

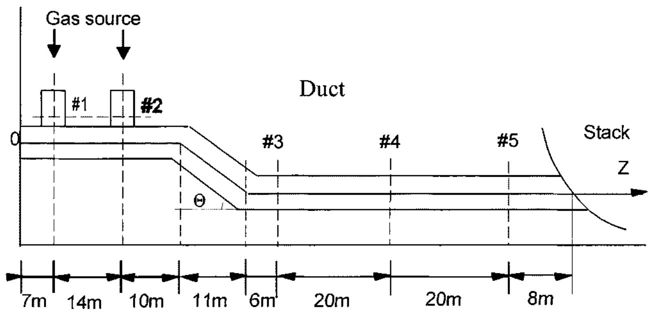

Fig. 2. Construction of the duct.

The volume flow rate at standard reference condition (i.e., 0 °C and 101.3 kPa) q_{vr} can be expressed as

$$q_{vr} = q_{vs}\left(\frac{273}{T_s}\right)\left(\frac{p_e}{101.3}\right).$$

B. Neural Network Modeling for the Optimization of Sensor Locations

A neural network model of flue gas flow has been discussed in [2], in which the flue gas flow rate was predicted with individual velocity and other variables of the operating conditions. The new neural network model presented in this paper is, in fact, the inverse model of that in [2]. This model can be used to predict individual velocity using the volume flow rate in the duct or stack, with its architecture shown in Fig. 1.

In Fig. 1, the input vector is defined as $[z\ \theta\ r\ flowrate]$, where $z, \theta,$ and r are the coordinates of the measurement point in a predefined coordinate system. The z axis represents the location of the sampling plane along the centerline of the duct. Due to the circular shapes of the duct cross-sections, the positions of sampling points in these sampling planes are represented as polar coordinates, θ and r. The flowrate is the volume flow rate in the duct or stack.

The velocity in the output vector is the individual velocity at the position $(z, \theta,$ and $r)$, corresponding to the volume flow rate, *flowrate*, in the duct or stack.

The model is used to generate the velocity profiles in each sampling plane based upon the individual velocities. The best sensor location is then determined according to the uniformity of the velocity profile.

C. Experiment

The neural network model was validated using experimental data from a case-study plant [5], as shown in Fig. 2, where the duct presents the following geometry: the gas inlets occur at an angle of 90° along two pipes measuring 5.5 m in diameter and 7 m in length. The flue gas flow is along a horizontal pipe of a diameter of 7.1 m for a distance of 31 m at the centerline. From this point there is a horizontal elbow of 39°54′ measuring a total 13 m in length. Downstream from this elbow, another 52 m long duct of a diameter of 7.1 m leads directly into the stack.

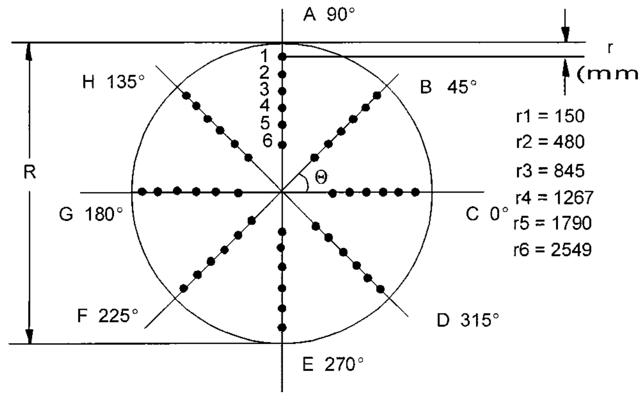

Fig. 3. Sampling plane.

There are five sampling planes (#1–#5) selected along the duct. In each sampling plane, four diameters were measured, with six sampling points on each radius (Fig. 3).

D. Training and Testing of the Neural Network

The model is based upon a three-layered feed-forward neural network, using the Levenberg-Marquardt training [6]. First, the data from all sampling planes were collected, and half of them were then randomly selected to train the neural network. Two kinds of tests were performed after the training:

Test 1—Using the trained data set,
i.e., those used in training
Test 2—Using the testing data set,
i.e., those not used in training

with the test results shown in Table I.

Two examples of Test 2 are given in Figs. 4 and 5, corresponding to sampling planes #1 and #4, respectively. In Fig. 5, the predicted velocity (dashed line) follows the measured velocity (solid line) quite well, even if these samples have never been met by the network before. It can be seen from the above testing results that:

1) There is not much difference in the Test 1 results, as the data have been used for the training of the neural network. Test 2 gives a better indication of the generalization ability of the neural network.
2) As the sampling planes #1 and #2 are near the gas inlets, the flue gas flows in these two planes are not stable enough, and the prediction errors are quite large (Fig. 4). In the sampling planes #3, #4, and #5, on the other hand, the gas condition is more stable, with smaller prediction errors (Fig. 5).
3) The test results have proved that this model can predict the individual velocity accurately if the flue gas flow is stable enough. This is necessary for this model to be used for optimizing the sensor locations.

TABLE I
TEST RESULTS WITH THE NEURAL NETWORK MODEL

Test	Sampling plane	Mean absolute error (m/s) (%)	Standard deviation (%)
Test 1	1	4.86	8.15
	2	2.76	3.36
	3	2.24	2.85
	4	2.52	3.29
	5	2.02	2.65
Test 2	1	26.67	88.97
	2	17.78	37.23
	3	3.45	4.29
	4	3.26	4.15
	5	2.53	3.16

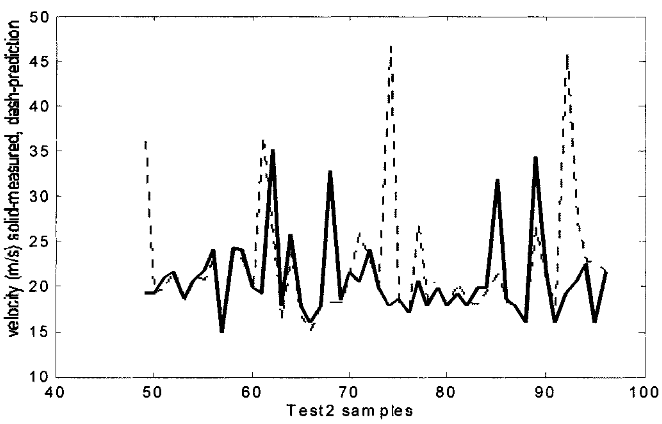

Fig. 4. Test 2 results in sampling plane #1.

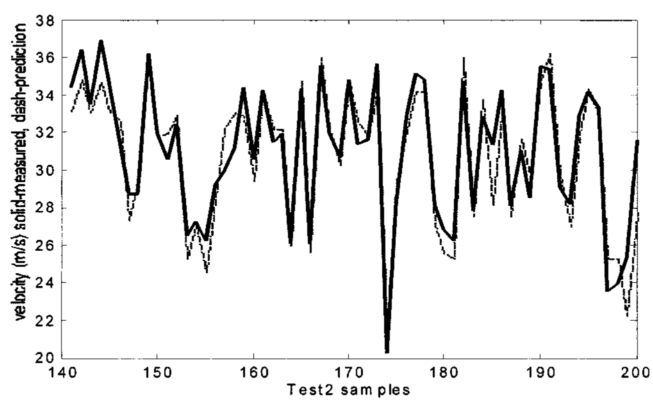

Fig. 5. Test 2 results in sampling plane #4.

III. OPTIMIZATION OF SENSOR LOCATIONS

A. Preliminary Consideration

According to the ISO 10780, sampling shall take place in a length of a straight duct with constant shape and cross-sectional area, and, as far as possible, downstream from any obstruction which may cause a disturbance and produce a change in the direction of flow. The section of straight duct should be at least 7 hydraulic diameters long. Over the length of the straight section, locate the sampling plane at a distance of 5 hydraulic diameters from the inlet. If the sampling plane is to be located in a duct near the gas stream exit there should also be 5 hydraulic diameters (making a straight length of 10 hydraulic diameters). The suitable sensor locations can be determined based upon the above requirements. As there are two inlet points and one elbow in this case, the sensors should be located between the sampling planes #3 and #5.

TABLE II
MAXIMUM DIFFERENCE BETWEEN THE AVERAGE VELOCITIES ACROSS EACH DIAMETER AND THE MEAN FOR ALL THE DIAMETERS IN EACH SAMPLING PLANE (#3–#5)

Sampling plane	#3	#4	#5
Diameter	B-F	D-H	B-F
Max difference	7.48%	0.74%	0.75%

B. Criterion

The optimization criterion may be derived from the ISO10780, that is, the difference between the average velocities across each diameter should not exceed 5% of the mean value for all the diameters in the sampling plane. If the difference exceeds 5%, additional sampling points shall be taken or a new sampling location should be selected.

C. Optimization

As the individual velocity and hence the velocity profile on each diameter in a sampling plane can be obtained from the above model, the best location can be determined by comparing the velocity profiles in the different sampling planes according to the above criterion.

With the velocity profile on each diameter in the sampling plane first calculated using the model, the maximum difference between the average velocities across each diameter and the mean for all the diameters in the sampling planes #3, #4, and #5 are presented in Table II. The predicted velocity profiles for these diameters, together with the experimental ones, are shown in Figs. 6–8.

As the difference between the average velocities across each diameter should not exceed 5% of the mean for all the diameters in each sampling plane, the sampling plane #3 is not suitable as a sampling plane. The best sensor location should be between the sampling planes #4 and #5.

To determine the optimum location further between the sampling planes #4 and #5, three additional sampling planes were selected in between, that is, planes A1 (30 m downstream from the last elbow), A2 (35 m downstream from the last elbow) and A3 (40 m downstream from the last elbow), as shown in Fig. 9.

As there was no experimental data in these additional sampling planes (A1, A2, and A3), the velocity profiles on each diameter in these additional planes can be predicted using the above neural network model. Again the maximum differences between the average velocities across each diameter and the mean for all the diameters in these sampling planes are calculated, as given in Table III.

The results in Table III indicated that the maximum differences between the average velocities across each diameter and

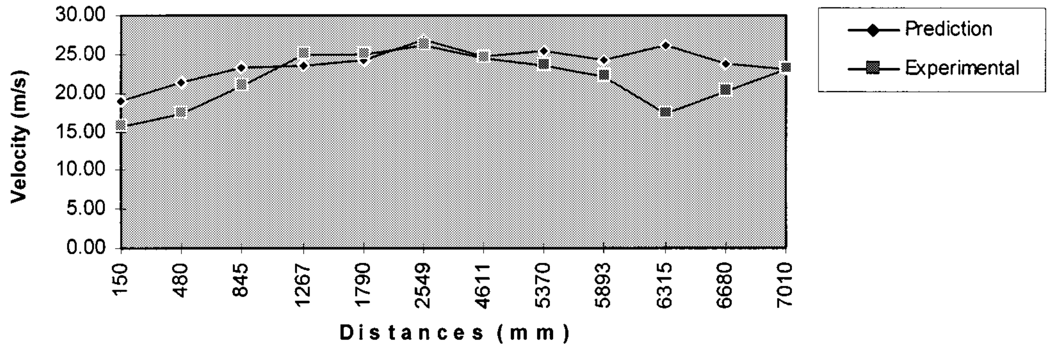

Fig. 6. Velocity profile on diameter B-F in sampling plane #3.

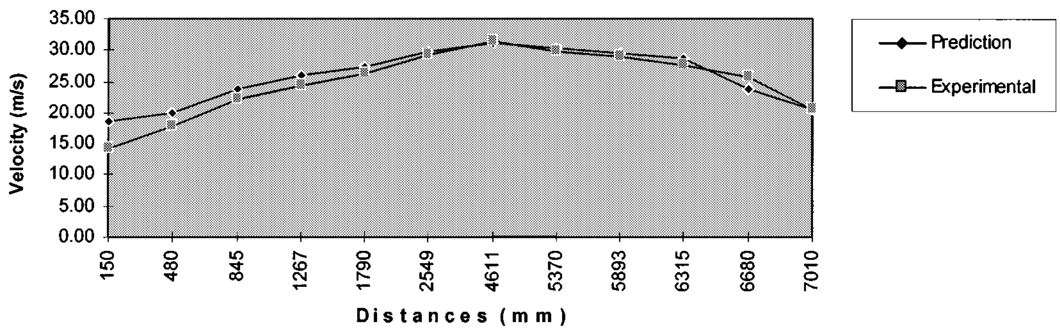

Fig. 7. Velocity profile on diameter D-H in sampling plane #4.

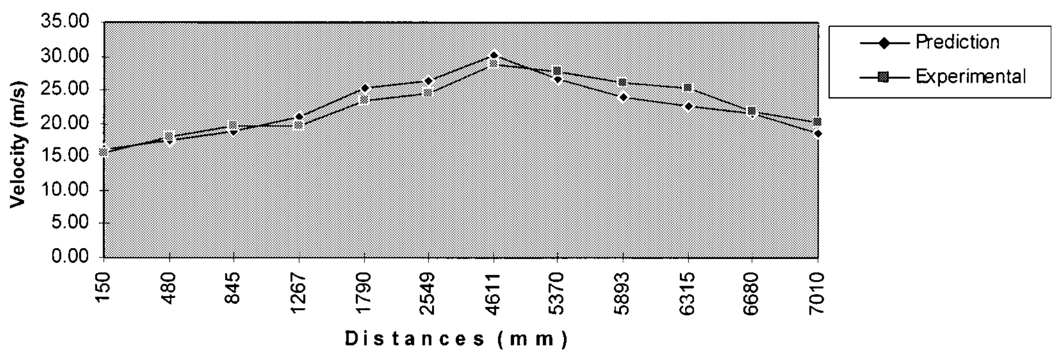

Fig. 8. Velocity profile on diameter B-F in sampling plane #5.

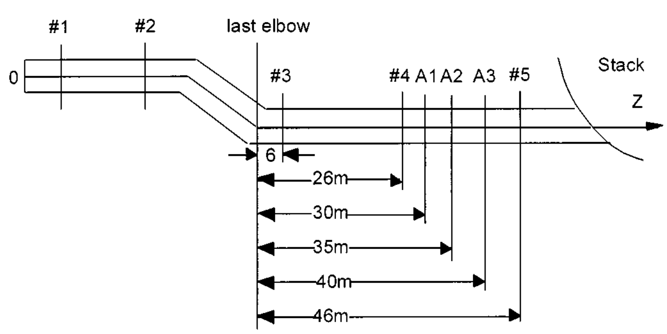

Fig. 9. Additional sampling planes between #4 and #5.

TABLE III
MAXIMUM DIFFERENCE BETWEEN THE AVERAGE VELOCITIES ACROSS EACH DIAMETER AND THE MEAN FOR ALL THE DIAMETERS IN EACH SAMPLING PLANE (A1–A3)

Sampling plane	A1	A2	A3
Diameter	A-E	C-G	A-E
Max difference	0.22%	0.23%	0.96%

the mean for all the diameters in sampling planes A1 and A2 are much less than those in other sampling planes. This is because the gas flow between these two sampling planes was well developed and the velocity profiles had a better distribution (Figs. 10 and 11). The segment between A1 and A2 (that is, 30–35 m downstream from the last elbow), therefore, should be the best sensor location for flue gas flow measurement.

IV. DISCUSSIONS AND CONCLUSIONS

A novel application of neural network modeling to the optimization of sensor locations in the industrial ducts and stacks has been discussed. With the method validated by experiment

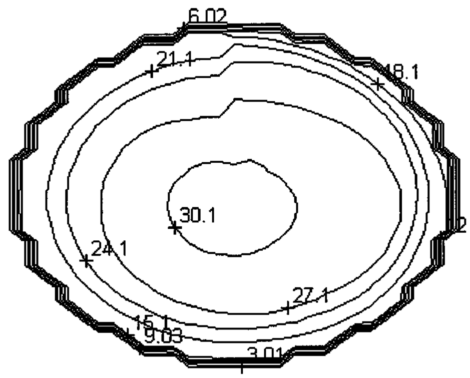

Fig. 10. Velocity contour 30 meters downstream from last elbow.

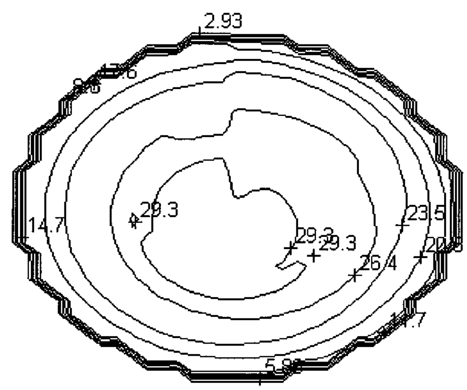

Fig. 11. Velocity contour 35 meters downstream from last elbow.

conducted at a case-study power plant, the following conclusions can be drawn from the above discussions:

1) The velocity profile of the flue gas flow in each sampling plane can be predicted using the proposed neural network model. According to a criterion derived from the international standard ISO 10780, the optimum sampling plane has been determined.
2) The relationship between the individual velocity and the volume flow rate modeled by the neural network is essentially based upon the experimental data from the real world. In order to achieve good predictions, it is necessary to have reliable and representative data which cover typical conditions of the system.
3) In the optimized sampling location in the case-study plant, the maximum difference between average velocities across each diameter is only 0.22%, much less than 5% as required in the above criterion. This means that a number of locations may be used as a sampling plane. It also implies that a smaller number of sampling diameters or points may be adequate, resulting in a reduced manual measurement operation.

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