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Use of Neural Networks in the Capacitance Imaging System

Technical Note

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October 1993

U.S. Department of Energy
Office of Fossil Energy
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MASTER

Abstract

The U.S. Department of Energy's Morgantown Energy Technology Center (METC) has developed a capacitance imaging system (CIS) to support its fluidized-bed research programs. The CIS uses 400 electric displacement current measurements taken between combinations of pairs of 32 electrodes to obtain a measure of the fluidized-bed material density in the volume between the electrodes. The measurements are simultaneously made for three other sets of horizontally-oriented 32 electrodes with the four sets evenly spaced vertically.

This report describes the development of a method of using the 400 current measurements per level as the input to a neural network to produce the 193-pixel density estimates defined for each level. A 417-neuron subnetwork using 4,047 weights is defined as the system used to determine a set of 32-pixel densities in one of the annular regions of the fluidized-bed cross section. The same subnetwork with different values of weights is used for the other five annular regions that cover the rest of the cross section. An averaging technique is used to determine the density of the small central region. The methods used to optimize the set of weights for each of the six subnetworks are described. The results of tests using calibration electric current data as inputs to the neural system showed that these density estimates have less error than three previously developed methods of converting current measurements into pixel density maps. A comparison of the density maps produced by the neural system and the alternate three methods using input fluidization data also indicates the superior performance of the neural network approach.

The developments described in this report build upon work described in a 1991 METC report by three of the authors entitled *193-Pixel, Three-Dimensional Capacitance Imaging System*, DOE/METC - 92/4109, NTIS/DE92001253.

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1 Introduction

This technical note is the fourth in a series that describes the development of the capacitance imaging system (CIS) from its inception as a 49-pixel, 1-level system to the present 193-pixel, 4-level instrument. While designed primarily for application in fluidized-bed, two-phase, bed-density measurement and imaging, it has multiphase materials flow monitoring capabilities as well. The third technical note of the series (Fasching, Loudin, and Smith 1991) describes the electronic system of the 193-pixel CIS and outlines its operation in producing data used to generate 3-dimensional density images from sets of 400 electric displacement current measurements. The third technical note also describes the three methods developed to convert these electric current data into 193-pixel density values at each of four levels at acceptable error levels. The first method was fast enough for real-time image display but had composite root-mean-square (rms) error ranging from 30 to 40 percent. The other two methods were too slow for real-time image display but reduced rms error in the range of 10 to 20 percent and were used for post-run analysis.

This fourth technical note describes the application of neural networks to the generation of 193-pixel density values from the same 400-measurement displacement current set through the use of a neural network. This development had the objectives of producing generation rates high enough for the method to be used for real-time image display and accurate enough to be used for post-run data analysis.

2 Background

The use of neural networks in imaging and pattern-matching applications is a fairly recent technological development. Some of the earliest works in this field in the 1950s was based upon studies of the structure and behavior of the brain and nervous systems of animals. This work led to the identification of the neuron or nerve cell as the basic building blocks of biological neural systems. Much of the behavior of systems of incredibly complex interconnected neurons is not understood in terms of the behavior of the individual neuron. However, earlier researchers used artificial neural network models using electronic-switching devices to model the neuron and used dense interconnection of these units in mimicking the structure of simple biological systems. With the development of fast, memory-intensive digital computers, the study of neural network models has shifted from the use of interconnected electronic devices to computer simulations of these models.

Books by Dayhoff (1990) and Wasserman (1989) present complementary summaries of the history and biological bases of neural networks and give overviews of the development of simple neuron electronic models into the interconnected neural networks of today. Their coverages include the design, training, and application of these networks in diverse fields without the use of the highly specialized mathematics found in the earlier technical literature. Both books follow the textbook approach in starting with the introduction of the simplest concepts and circuits, then building upon these to arrive at the description and analysis of the more complicated, interconnected systems of high capability. Denning (1992) gives a briefer history and summary of neural network capabilities and suggests references for further study.

Lippmann (1987) provides an introduction to artificial neural networks through analysis and discussion of six neural network models that are applied to pattern classification. Hopfield and Tank (1986) define a nonlinear dynamic neural model and apply an energy minimization principle to gain insight into operational properties of the network. Tank and Hopfield (1986) describe how several sample optimization of solution problems can be solved by densely interconnected networks of simple analog processors. Tomlinson, Walker, and Sivilotti (1990) describe the application of a pair of integrated circuit chips that can be used to build neural networks of arbitrary topography and extremely broad dimensions.

More practice-oriented discussions of the application of neural networks are appearing in the literature. Masory and Aguirre (1990) discuss the application of neural networks in sensor calibration procedures. Studt (1991) gives a lay perspective of neural networks, their training, and prospective applications. Ross (1991) describes work done in emulating the neural behavior of the inner ear and the application of the results of this work in gaining insights into the behavior of biological neural systems. Abu-Mostafa and Psaltis (1987) discuss the application of optical technology and its dense interconnection capability to neural network construction, which requires an extensive set of interconnections.

The theory used to determine 193-pixel density estimates from 400 interelectrode current measurements using other than neural network techniques is given in the technical notes by Fasching and Smith (1988, 1990) and by Fasching, Loudin, and Smith (1991).

3 Theory

Much of the theory developed during neural network research is given in the texts and papers discussed in the Background section. Here, we present a summary of one of the accepted means of varying neural network parameters to improve network performance. This will provide the background and a comparison for the procedure used in our work as described in the Network Training section.

Figure 1 shows a single-layer neural network having 400 input nodes and an offset (or bias) node. The network accepts 400 input currents and a fixed bias level, multiplies each of the input current values I_i by its own weight value $W_{i,N}$ and presents the resulting weighted values of current $W_{i,N} I_i$ and the bias value B_j to the summing node Σ with $i = 1, 2, 3, \dots, 400$ and $j = 1, 2, 3, \dots$, number of last layer. The nonlinear function F acts on the weighted sum and provides the normalized output D_N , which is the network's estimate of the bed density at pixel N . The nonlinear expression F is usually the sigmoid function defined as

$$F = \frac{1}{1 + \exp(-\Sigma W_{i,N} I_i)} \quad (1)$$

where F nonlinearly approaches zero for decreasing (negative) values of the sum of weighted current values and nonlinearly approaches one for increasing (positive) values of the sum.

During network training, the period in which the weight values are changed to produce D_N density estimates closer to the true value $D_{N \text{ Standard}}$, the feedback loop that includes the Back Propagation Control (BPC) is used. One of the inputs to this control unit is $D_{N \text{ Standard}}$, which is the true value of the density of the pixel being estimated using the 400 input currents. The BPC uses the true value of density and the estimated value D_N to compute the error δ_k as

$$\delta_k = D_k(1 - D_k)(D_{k \text{ Standard}} - D_k) \quad (2)$$

where $D_k(1 - D_k)$ is the slope of the function F and $(D_{k \text{ Standard}} - D_k)$ is the error in density for pixel k . The individual weights are adjusted from their initial values $W_{i,N}(t)$ to a new value $W_{i,N}(t + 1)$ using the relation

$$W_{i,N}(t + 1) = W_{i,N}(t) + \eta \delta_k I_i, \quad (3)$$

where η is a constant introduced in the BPC system. Initial values of weights are chosen as described in the literature using a variety of methods. One approach is to randomly select values within some preset range. Another approach is to use the same value for all weights, with this value taken as a test variable from trial to trial. Several approaches to the weight

adjustment procedure are described in the literature (Dayhoff 1990; Wasserman 1989). One method, described very generally here, is to select randomly the weight to be adjusted for a set value of η , compute the new value of the output D_N , and then retain the new weight if the error in D_N is less than it was before weight adjustment, otherwise the weight value before adjustment is retained. The next weight is selected from the remaining pool of unadjusted values and the adjustment-output error calculation-retention/-rejection process is repeated. This procedure is continued until all weights have been adjusted. The value of η is changed (usually made smaller) and the weight adjustment cycle is repeated. This procedure continues until the output error reaches acceptable limits or until no significant error reduction occurs from one complete iteration through the weights to the next iteration.

Figure 2 shows a multilayer neural network of the type used in our work with a hidden layer of neurons shown explicitly and not implicitly as in Figure 1. A popular method for adjusting the weights of the hidden layer is given in the more general form of the back-propagation procedure. First the error δ_k is computed for every neuron in the output layer as described above. Then the error δ_k is propagated back through the same weights to generate an error δ for each neuron in the hidden layer adjacent to the output layer. The values of these δ s are then used to adjust the weights of this hidden layer. This process is repeated to propagate errors backward and to adjust weights of all proceeding layers back to the input.

4 Experimental Neural Networks

Method 7 was one of the first methods developed at METC during early experimentation with the application of neural networks to use the capacitance-imaging system (CIS) image production. This method used the 193 density predictions of Method 1 given by a term $[\Delta I_i \Delta I_j]^{1/2}$ for each of the pixels as described in earlier technical notes (Fasching and Smith 1990; Fasching, Loudin, and Smith 1991), where the ΔI s are the normalized CIS inter-electrode current values found to produce the best estimate of each of the 193-pixel densities. These density predictions are used with a bias value as the inputs to 194 input neurons, each of which use a sigmoid function to produce an output. These inputs use 103 weights, and system symmetries, which allows some of the weights to be used more than once, to produce the inputs to a 10-neuron hidden layer. The outputs of the hidden layer plus that of a hidden layer bias node are each multiplied by its own weight value and serve as the input to the output node. This gives a total of 114 weights to be optimized. The sum of the weighted inputs from the hidden layer and its bias node is acted on by the sigmoid function of the output node to produce the density estimate of the lowest numbered pixel in one of the rings (B, C, D, E, F, or G) in Figure 3. The density estimates for the other 31 pixels in the ring are found using the same neural network and the same 114 weights (once optimized as described in the Network Training section) with the ordered input $[\Delta I_i \Delta I_j]^{1/2}$ values incremented the proper number of steps in the order required by the circular symmetry of the ring. The procedure is repeated for the remaining rings using the same ordered input values of square-root-of-current-product and the same neural network configuration, but with a different set of optimized weights. The weight optimization process used was a variation on the back propagation method for error reduction. More detail on a procedure similar to this that was used for Method 9 is given in the Network Training section.

Instead of using the square-root-of-current-product inputs of Method 7, the neural network used in the procedure entitled Method 9 used the set of 400 displacement currents of the CIS as inputs. The neural subnetwork for one of the rings (B through G) in Figure 3 is illustrated in Figure 4. In this figure, there are 400 input neurons or nodes which accept the ordered array of 400 normalized displacement currents as inputs. The output of each of these input neurons plus that of the input layer bias neuron is connected to the input side of each of the 10 neurons of the first hidden layer. Each of these 4,010 connections has a unique weight associated with it. For example, the input to neuron 2 of the input layer is ΔI_2 ; the output of node 2 provided to neuron 1 of the first hidden layer is $W_{L1,2-1}\Delta I_2$, to neuron 2 is $W_{L1,2-2}\Delta I_2$, to neuron 3 is $W_{L1,2-3}$, ..., and to neuron 10 is $W_{L1,2-10}\Delta I_2$. The output of each of the neurons in the first hidden layer plus that of the bias neuron in this layer are fully connected (the output of each neuron in the first hidden layer is connected to the input of each neuron in the next layer) to the three neurons of the second hidden layer using 33 weights for the 33 interconnections. The three neurons of the second hidden layer and the associated bias neuron are connected to the output neuron using four weight values, giving a subnetwork total of 4,047 weights. Each of the 417 neurons (the sum of the 400 input neurons, the three bias neurons, the 13 hidden layer neurons, and the output neuron) in this subnetwork accepts its own set of weighted inputs, sums these inputs, then provides an output that is the value of the

sigmoid function evaluated at the value of the weighted input sum. The output of the subnetwork is designated as the normalized pixel density ΔD_j in Figure 4. For one particular ordered set of 400 input currents and the set of 4,047 weights (optimized as described in the Network Training section) for a particular ring ΔD would be ΔD_{B1} , ΔD_{C1} , ΔD_{D1} , ΔD_{E1} , ΔD_{F1} , or ΔD_{G1} .

In general, the subnetwork configuration for each ring would be the same, but the corresponding values of the 4,017 weights for each ring would, in general, be different. Then for a given ring, the ordered set of 400 current values would be reordered in accordance with the circular and diametric symmetries (Fasching and Smith 1990; Fasching, Loudin, and Smith 1991) of the cross section of the CIS. The reordered input would produce the estimate of the second pixel density ΔD_{B2} , ΔD_{C2} , ..., or ΔD_{G2} . The order of the 400 input currents is changed in steps designed to satisfy system symmetries to produce output values ΔD_j , ranging from $j=1$ to $j=32$. The same procedure is used for each of the six rings to obtain normalized density estimates for the 192 pixels in these rings. Several simplistic, relative to the ring density method, approaches using neural networks to obtain density estimates for pixel A (pixel 1) were tried with generally unsatisfactory results. This is consistent with the results obtained using Methods 1, 2, and 3 [Fasching and Smith (1988, 1990) and Fasching, Loudin, and Smith (1991)] and is considered to be associated with the low sensitivity of interelectrode current change to changes in density in the central region of the cross section. Method 9, therefore, uses the average of the adjacent B ring normalized densities as the estimate for the normalized density value for pixel A.

Figure 5 shows a condensed representation of 192 subnetworks, each of the design given in Figure 4, that can be used to generate estimates of the 192-pixel densities in rings B through G. The density estimate for pixel A is taken as the average of the 32 values of ΔD_{Bj} . The reordering of the 400 input current values in determining the pixel densities in each ring is indicated in general terms and is not necessarily the actual stepwise/reordering procedure.

Figure 5 represents a complete neural system for obtaining density estimates for the 192-pixel density values in the six rings of a CIS cross section. The system can be realized either in hardware or software. In either realization, the system could range from the simplest, consisting of only one neural subsystem (Figure 4), to the full-scale implementation given in Figure 5. In the simplest case, the weights would be set at the optimum values for one of the rings, say the B ring. The input current values would be set to the value for the first pixel, say B1, and the value of ΔD_{B1} obtained and stored. The input currents would be reordered in steps to obtain the rest of the B-ring density values through ΔD_{B32} . The weight values would be changed to the set that is optimum for another ring, say the C ring. The input currents are then cycled through the ordering and reordering steps used in the B-ring procedure to obtain the values of ΔD_{C1} through ΔD_{C32} . The change to the weight set that is optimum for the next ring, and subsequent stepwise application of ordered input currents, is repeated for the remaining rings. The density at pixel A is found as the average of the 32 B-ring values. The full-scale implementation (Figure 5) would have 192 neural network subsystems (Figure 4).

The set of weight values in each row (ring) of Figure 5 is the same for each subsystem in the row and is ideally optimum for that row (i.e., produces an acceptable density estimate at the output). The order of the input currents in the first column of Figure 5 are the same for each subsystem in this column, with the order chosen to produce output density values for pixels B1, C1, ..., G1. The order of input currents to any column is the same and is selected to produce density values of B2 through B32, C2 through C32, ..., G2 through G32. Tradeoffs between speed of density determination and system complexity and associated cost can be made to find the compromise system somewhere between the two extremes of the simplest case using one subnetwork, and the full-scale implementation using 192 subnetworks that is optimum for a particular application. In the computer simulation of Figure 5 reported here, the density values were determined serially in an order of pixels, such as B1, B2, ..., B32; C1, C2, ..., C32; D1, D2, ..., D32; E1, E2, ..., E32; F1, F2, ..., F32; and G1, G2, ..., G32, and A as the average of the B-ring values.

5 Network Training

The training process for the CIS density-imaging neural network requires sets of 400 measured interelectrode current values and the corresponding 193 known pixel density values both obtained during calibration procedures (Fasching and Smith 1988, 1990; Fasching, Loudin, and Smith 1991). In general, the training procedure starts with the application of the normalized current values to the input to the neural network, which then generates the 193-pixel normalized density value estimates. These density estimates are used with the known density values to obtain the error for each pixel. Then the weights associated with the interconnections in the neural network are adjusted to minimize the overall density error. This section gives details on the procedures used in this minimization-of-error process.

The development of the neural network weight adjustment procedure for the CIS was initiated using the network of Method 7. The training data sets were those used in the calibration of Methods 1, 2, and 3. Each of the training data sets consists of 400 current measurements from which the 193 density estimates were obtained and the corresponding 193 known values of pixel density. Although the density values for all 193 pixels were known for each of the 10 tests of Method 7, the square-root-of-current-product density estimates and the corresponding known 32-pixel densities were used in a one-ring-at-a-time weight adjustment procedure. The use of only these 10 sets of data was necessitated by the lack of access to laboratories and the CIS because of complete shutdown for over a year of such activities at METC as a result of a DOE Tiger Team visit.

The training sets for Method 7 consisted of square-root-of-current-product and density data for the eight 1- and 2-circular void calibration procedures for Methods 1, 2, and 3 (Fasching and Smith 1988, 1990) and the two sets obtained for an empty bed ($D=1$ for each pixel) and a flat bed ($D=0$ for each pixel). This definition of $D=0$ for maximum normalized pixel density and $D=1$ for zero normalized pixel density was introduced early in the CIS program so that bubbles (true low density) would stand out in density plots or maps. In addition, for convenience in plotting density values, a scaling factor is used with the normalized density so that $D=1$ becomes $D=1,000$. During the early stages of the development network training procedures, the 114 weights were placed in a pool. One weight was picked using a random selection process, which is initiated by the random selection of a seed value. The weight value was adjusted for minimization of composite rms density error (defined at the beginning of the next paragraph) or was restored to its initial value if no error reduction was obtained with the weight returned to the pool of weights. Once back in the pool, the returned weight had the same chance as the others for being selected for adjustment. The selection/adjustment process continued for 114 selections, defined as one iteration, and was repeated for the 19 additional iterations that made up one defined training period. The composite error value was checked at the end of each training period, and the process was continued if satisfactory error reduction over the period resulted or stopped if zero reduction was obtained over the last training period.

The composite rms density error for the ring of pixels under consideration is defined as

$$\text{Error} = \left[\frac{1}{32N} \sum_{j=1}^{j=N} \sum_{i=1}^{i=32} (\Delta D_{xi} - \Delta D_{yi})^2 \right]^{1/2} \quad (4)$$

where N is the number of training sets ($N=10$ for Method 7), ΔD_{xi} is the known normalized density of pixel i , and D_{yi} is the neural network estimate of the normalized density of pixel i and i runs from 1 to 32 for each ring.

The first try at error minimization through the variation of the value of one weight in the multistep procedure described above can be outlined as follows:

1. Each of the 114 weights is set to a random value (with uniform distribution) between $-\frac{2}{193}$ and $+\frac{2}{193}$.
2. A randomly selected seed value sets the random sequence over which the network weights will be adjusted and the first weight is drawn.
3. The weight value is increased by the value 0.005, and the composite rms error using the new weight value is calculated.
4. If the error is reduced, the weight value is changed to the new value, then returned to the pool and the next weight in the sequence is drawn from the pool for adjustment.
5. If the error is not reduced, the weight value is reduced by 0.005, the composite rms error is computed, and the new weight value is retained if error reduction is obtained; otherwise, the weight is restored to its original value and returned to the pool.
6. This procedure was continued until completion of the 114 sequence-of-weight adjustments was accomplished.

Early in the development of the adjustment process, smaller (e.g., ± 0.002 then ± 0.001) changes were made in the weights after the ± 0.005 change was used and the weight value producing the smallest error was retained. The multiple incremental change process, which was costly in computer time, was abandoned after the parabolic error reduction technique described now was developed.

Figure 6 illustrates error reduction in composite rms pixel density by variation of a weight value using the parabolic method. The error ERF_1 is computed for the initial, randomly selected, weight value W_i . A selectable small increment (e.g., 0.005, 0.002, or 0.001) is used to determine the two values, $W_i \pm \Delta W_i$, which are then used to find ERF_1 and ERF_2 . These three points determine the parameters defining the parabola passing through these points. The error minimum ERF_{MIN} defined by this parabola is then used to find the value

W_{MIN} of the weight producing this minimum. Then W_{MIN} is used as the new value of the weight that is returned to the pool of weights.

The weight optimization process for Method 9 evolved from that outlined above for Method 7. The first step in this process was the setting of the initial weights for the subnetwork for one of the rings (Figure 4) whose weights are to be optimized. The procedure outlined here is repeated for each of the other five rings later in the process.

The calibration data consists of the sets of 400 interelectrode current measurement values for each of the following known bed density conditions: four elliptical voids of different sizes at four different test positions near the vessel wall; the eight one- and two-circular void tests described in the Method 7 calibration; one circular void at the center of the vessel; and a 4-test linearization calibration using the measured currents and $D=1,000$ value for all pixels for the flat bed, plus three calibration tests using $D=100$, 400, and 700 and corresponding currents of 10, 40, and 70 percent, respectively, of the $D=1,000$ current set. This gives a total of 17 calibration tests against which the rms composite pixel error is to be minimized for each ring. This error is defined in Equation 4 with $N=17$, the number of calibration tests.

1. The outputs of the three bias nodes are set to 1,000 (scaled from 1) and the 14 weights, W_{B1-1} through W_{B3-1} , are set equal to zero.
2. The 4,000 weights of the input layer, $W_{L1,1-1}$ through $W_{L1,400-10}$, are each set to random values between -0.048 through 0.053. The 30 weights of the first hidden layer, $W_{L2,1-1}$ through $W_{L2,10-3}$, are each assigned random values between -0.3 to 0.5. The three weights at the output of the second hidden layer, $W_{L3,1-1}$ through $W_{L3,3-1}$, are each given random initial values between -1 through 1.67. This gives a total of 4,033 weights, which together with the 14 bias neuron weights gives a total of 4,047 weights to be adjusted for minimum composite error.
3. Each of the 4,047 weights is assigned one of the positions in the 4,047-slot sequence making up the weight pool.
4. A seed value, which defines the random order in which the weights are selected from the 4,047 position sequence for adjustment, is randomly selected. Once a weight is selected and adjusted, it is returned to the pool where it has the same probability of being selected on the next draw as the other 4,046 weights.
5. The first weight W_1 is selected and the composite error ERF_1 using this weight is computed; the errors ERF_1 and ERF_2 are computed for $W_1 \pm 0.001$ and the parameters of the parabola in Figure 6 are determined.
6. The minimum value of the parabola ERF_{MIN} and the corresponding weight W_{MIN} are computed. If the value of ERF_{MIN} is less than ERF_1 , the weight value W_{MIN} is retained for a further test.

7. The densities using this new weight and the other 4,046 weights in the pool are computed for the ring being optimized. Scaled allowed density ranges of -50 to 1,050 up to -200 to 1,200 serve as the second go/no-go test. The widest range is used for the inner ring B, and the narrowest range is used for the outer ring F for the seven fluidization test pixel densities and for the 17 calibration tests during the initial part of the optimization procedure. The density values for the rings in between B and F were limited to ranges between these extremes. The density values are estimated by the network using measured currents, and if they all lie within the appropriate range for measured currents from the 17 calibration tests and seven fluidization tests, the new weight W_{MIN} is returned to the pool. If the test is not satisfied, the procedure in steps 5 and 6 is repeated for $W_i \pm$ a selectable smaller increment than 0.001. This increment is the value 0.001 times a factor that is inversely proportional to the estimated density value and directly proportional to the nearest density range edge value. If this test does not produce a density value within the specified range, the original weight value is returned to the pool.
8. The process is continued for one training period, which consists of 20 iterations. One iteration is defined as 4,047 adjustments of weight values as outlined in steps 5, 6, and 7.
9. Some further tests of progress in error reductions are made to avoid a poor sequence of weight selection during the optimization process. These tests consist of the following steps:
  - a. After 10 initial weight adjustments, the rms composite error must be less than 50 percent for continuation. If it is not, the process returns to step 1.
  - b. After 200 initial weight adjustments, the error must be less than 25 percent; otherwise, the procedure returns to step 1.
  - c. After any consecutive 4,047 weight adjustments, the process returns to step 1 if zero error reduction has been obtained.
10. After every 20 iterations of satisfactory error reduction, a new seed is randomly selected and the process continues until a satisfactory composite error is obtained or a preset reasonable training time period has been completed.

The optimization process is accomplished for the other five rings, and if a seed value is found for a ring that gives rapid error reduction, it is tried on the rings adjacent to the test ring.

6 Results

The pixel densities predicted by the neural network for the 400-set current measurements of two calibration tests and a fluidization test are given in this section. The calibration tests are two of those used in the optimization of the weights in Method 9, in the determination of the constants in the equations of Methods 2 and 3, and in the choice of the two currents used in the square-root-of-current-product estimate of pixel density in Method 1. For the two calibration tests, plots of the 193 true pixel densities are given. Each of these are followed by plots of the densities predicted by Methods 9, 1, 2, and then 3. Since true pixel densities for the fluidization test are not known, only the pixel densities predicted by Methods 9, 1, 2, and 3 are presented and compared.

Figure 7 gives the true pixel density for the calibration procedure, which used a 3-inch nylon cylinder placed near electrode 23 (Figure 3) in the empty fluidized-bed vessel to simulate a void. Figures 8, 9, 10, and 11 show the pixel density estimates obtained using the 400 current set obtained during this calibration procedure and the data processing provided by Methods 9, 1, 2, and 3, respectively. Comparison of these figures indicate that Methods 9 and 3 appear to produce the best estimates of the densities given in Figure 7. Method 1 predicts densities low by a factor of 2 to 3, and Method 2 is troubled by predictions of negative (density larger than that of the flat bed) densities. Table 1 gives the error in the density estimate for each of the methods. The extremely good value of error for Method 3 is typical for tests in which Method 3 is used to predict the known calibration densities of tests that were used in optimizing the constants of the method. However, when Method 3 was used on test data not used in its optimization, the error ranged from 10 to 30 percent.

Table 1. Pixel Density Composite Error, One-Void Calibration Test

Method	rms Error (percent)
1	33.5
2	12.2
3	0.6*
9	7.8**

* Typically, small error values obtained for data used in calibration process; larger error obtained for data not used in calibration.

** This value has been reduced to about 5.7 percent since the 7.8 percent test was completed.

A two-void calibration test using the 3-inch nylon rod near electrode 23 again and a 1.5-inch nylon rod near electrode 5 produced the theoretical pixel density values shown in Figure 12. The density estimates produced by Methods 9, 1, 2, and 3 using the 400 current set obtained during this calibration are given in Figures 13, 14, 15, and 16, respectively. The numerical values of the composite error in these estimates are given in Table 2. Again, Method 3 does extremely well on data it has "seen" before. Again, the results appear to be the best for Methods 9 and 3, and Method 2 has negative value and irregular variations on peaks and at the baseline. Method 1 indicates proper density variations between density peaks and low values. Due to this property of showing density trends via a rapid computational method, it has proved useful in the real-time density display system. Much experience was gained while comparing density estimates of Methods 9, 2, and 3 as more calibration data were added and used in the adjustment of the weights and coefficients used in these methods. This experience indicates that further calibration data, particularly expanding to multivoid calibrations, would improve the density estimates of these methods. Method 9 in particular showed dramatic improvement, and such tests would produce more confidence in the results of fluidization tests using this method.

**Table 2. Pixel Density Composite Error,
Two-Void Calibration Test**

Method	rms Error (percent)
1	36.1
2	5.1
3	0.8
9	6.2*

* This value has been reduced to about 4.7 percent since the 6.2 percent test was completed.

For the results of the fluidization tests presented next, we can give no composite error for the pixel density estimates produced using each of the four methods. Instead, one frame (the density estimates produced by one complete cycle of 400 current measurements during a 20-second fluidization test), number 288, of density estimates produced by each of the four methods is presented for comparison and comment.

Figures 17 and 18 show the rectangular and polar plots (maps) of the pixel density estimates provided by Method 9 using the "best" set of weights found during the earlier calibration process. A series of 20 seeds was the starting point for the generation of twenty 4,047-weight sets used in the neural network of Method 9. The composite error for each set was computed and used to arrange the sets in a sequence in which the first or "best" set

produced the least error, and the last set produced the most error. Figures 17 and 18 used the first set of weights in the 20-set sequence. Then, the density estimates for each of the first seven sets were calculated, and the averages for each pixel were calculated with the resulting pixel density map given in Figure 19. The smoothing or filtering effect of the averaging process can be seen in comparing Figures 17 and 19, but no definite statement as to which plot best approximates the true density map can be given. However, we might expect the averaged plot to give the best overall estimate from the usual effects of the averaging of experimental data in increasing the signal-to-noise ratio. This is further seen in Figures 20 through 42 where rectangular density plots for Frames 280, 288, 295, and 315 are each given for averages of 10, 15, 18, and 20 pixel density estimates. Polar plots are also given in Figures 32, 33, 34, and 35 for the four frames in which the rectangular plots showing the average of the 18 best pixel density solutions were used. Three other frames (335, 345, and 355), each using the average of 18 Method 9 solutions for pixel density, were used in the polar plots of Figures 40, 41, and 42. These show the density change over two 10-frame intervals for an extremely low average bed density. The same increase in the smoothing of pixel density from pixel to pixel in a ring and at the transitions from one ring to another is seen more easily in the rectangular plots as the number of density values used in the average is increased. However, it also appears, from the limited data available here, that there is an upper limit in the number of density sets used in the averaging for increased smoothing of the plots. For example, the results produced using 20 density data sets appear less continuous (smoothed or filtered) than the results for the averages of 18 data sets. This supposed property of the averaging procedure was not investigated further because of time limitations.

Figures 43, 44, and 45 show the density maps resulting from the application of Methods 1, 2, and 3, respectively, to Frame 288 displacement current measurements. Figure 43 gives the lower-than-expected values of density estimates resulting from application of Method 1. It also displays the smoothing (low-pass filtering) action that has been noted to be typical of the method. The map in Figure 44 produced by the Method 2 solution-of-equation procedure shows the peaks and valleys at about the same place as the other three maps (those of Methods 9, 1, and 3). It also shows the lack of filtering property of Method 2 illustrated in the pixel-to-pixel abrupt density changes over the peaks and valleys of the density map. Figure 45 presents the results of averaging the density estimates produced by the nine "best" sets of coefficients for the Method 3 model. See Fasching, Loudin, and Smith (1991) for details on this model.

The 400 CIS interelectrode current measurements are composed of 25 fundamental equations plus 375 equations derived from the fundamental ones by use of rules involving the circular symmetry of the density map. All combinations of the set of 25 equations taken eight at a time were determined. Each set of eight, and the other equations derived from these eight, were used to define a Method 3 model. The coefficients of each of these models were optimized using ten 1- and 2-void calibration procedures. The models were used to predict the density map for one of the 2-void calibrations, and the nine models producing the least rms density map error were identified. Each of these nine models was used with the Frame 288 electric current measurements to produce pixel density estimates. The average of the nine density values for each pixel is shown in Figure 22. This method has been tested against calibration data sets that were not used in the model optimization process. In these cases where the density estimates could be measured against the corresponding known density

values, Method 3 was found to produce results better, in general, than those of Methods 1 and 2, but inferior to those produced by Method 9. Although numerical comparison of the density estimates for the fluidization tests for each of these methods cannot be given, tests like those described using calibration data appear to indicate that the neural network approach produces the best density estimates of the four.

All of Methods 1, 2, 3, and 9 calibration tests and optimization procedures were run using the level 1 portion of the CIS system. The resulting models were then used with the data gathered by all four levels to produce four 2-dimensional pixel density maps for the 3-dimensional display. The results of a check to see if it was appropriate to take the approach of extending level 1 calibration to the other three levels is given in Tables 3 and 4. These tables give the values of the rms composite error for each of the six rings at each of its four levels for the one-void and two-void calibration. While the error is about the same at each level for a particular ring, there is a general, small increase in error value from level 1 to level 4. This increase is thought to be produced by a small tilt in the rods used to produce the void simulations. This tilt would cause the true pixel density map during calibration to differ increasingly from level 1 to level 4.

**Table 3. Variation in Calibration Error with Level
One-Void Calibration -- Method 9**

Level	Ring (percent error)					
	B	C	D	E	F	G
1	4.6	6.1	5.1	5.6	5.0	2.0
2	6.1	6.7	5.7	6.7	6.3	2.1
3	6.2	6.9	6.0	7.2	7.0	2.2
4	6.9	7.4	6.5	7.6	7.1	2.3

**Table 4. Variation in Calibration Error with Level
Two-Void Calibration -- Method 9**

Level	Ring (percent error)					
	B	C	D	E	F	G
1	4.6	3.6	4.8	3.4	2.6	2.1
2	5.7	4.2	5.7	4.3	3.6	2.4
3	5.3	4.0	6.2	4.5	4.0	2.6
4	5.9	4.8	6.9	5.2	4.0	3.0

7 Conclusions and Recommendations

When used in fluidized-bed density monitoring/measurement, Method 9 offers advantage over the three previously developed methods. Method 1 has the largest error but is accurate enough for real-time display purposes since it rapidly converts current measurements into density maps. Methods 2 and 3 have produced less error than Method 1, but since they are too slow for real-time applications, they have been used for more accurate post-run analysis. Method 3 has shown promise of producing more accurate results using a density-averaging technique. However, the accuracy has been found to suffer when used to predict calibration density maps whose electric current data were not used in the model optimization process. Method 9 was found to produce density maps with about the same degree of accuracy as Method 3 when confronted with calibration data that it has seen before (used in the model optimization process). When tested with new calibration data, it produced density estimates with errors much less than any of Methods 1, 2, or 3.

The application of neural networks to CIS density imaging should be pursued. The error in density estimates should be reduced through use of more and more accurate and broader training data designed to produce density maps having conditions that better approximate the fluid-bed conditions to be monitored. To keep this increase in training economical, faster methods of accomplishing network training need to be developed.

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Figure 1. Back Propagation Control of Node Weights and Offset

Number of inner nodes (N) can be varied to meet application requirements

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Figure 2. First-Generation CIS 3-Layer Neural Network

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Figure 3. Pixel Identification for CIS Cross Section

Figure 4. Subnetwork of CIS Imaging Neural Network

Note: Density estimate of pixel A is average of 32 B-ring estimates

Figure 5. Neural Network for CIS Density Map Generation

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Figure 6. Parabolic Optimization of Neural Network Weights

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Figure 7. One-Void Calibration Pixel Density Map

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Figure 8. One-Void Pixel Density Estimates Using Method 9

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Figure 9. One-Void Pixel Density Estimates Using Method 1

Figure 10. One-Void Pixel Density Estimates Using Method 2

Figure 11. One-Void Pixel Density Estimates Using Method 3

Figure 12. Two-Void Calibration Pixel Density Map

Figure 13. Two-Void Pixel Density Estimates Using Method 9

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Figure 14. Two-Void Pixel Density Estimates Using Method 1

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Figure 15. Two-Void Pixel Density Estimates Using Method 2

Figure 16. Two-Void Pixel Density Estimates Using Method 3

Figure 17. Fluidization Pixel Density Estimates Using Method 9

Figure 18. Polar Map of Fluidization Density Estimates Using Method 9

Figure 19. Fluidization Pixel Density Estimates Using Seven Method 9 Averages Per Ring

Figure 20. Fluidization Pixel Density Estimates Using Ten Method 9 Averages Per Ring -- Frame 280

Figure 21. Fluidization Pixel Density Estimates Using Ten Method 9 Averages Per Ring -- Frame 288

Figure 22. Fluidization Pixel Density Estimates Using Ten Method 9 Averages Per Ring -- Frame 295

Figure 23. Fluidization Pixel Density Estimates Using Ten Method 9 Averages Per Ring -- Frame 315

Figure 24. Fluidization Pixel Density Estimates Using Fifteen Method 9 Averages Per Ring -- Frame 280

Figure 25. Fluidization Pixel Density Estimates Using Fifteen Method 9 Averages Per Ring -- Frame 288

Figure 26. Fluidization Pixel Density Estimates Using Fifteen Method 9 Averages Per Ring -- Frame 295

Figure 27. Fluidization Pixel Density Estimates Using Fifteen Method 9 Averages Per Ring -- Frame 315

Figure 28. Fluidization Pixel Density Estimates Using Eighteen Method 9 Averages Per Ring -- Frame 280

Figure 29. Fluidization Pixel Density Estimates Using Eighteen Method 9 Averages Per Ring -- Frame 288

Figure 30. Fluidization Pixel Density Estimates Using Eighteen Method 9 Averages Per Ring -- Frame 295

Figure 31. Fluidization Pixel Density Estimates Using Eighteen Method 9 Averages Per Ring -- Frame 315

Figure 32. Polar Map of Fluidization Density Estimates Using Average of Eighteen Method 9 Densities -- Frame 280

Figure 33. Polar Map of Fluidization Density Estimates Using Average of Eighteen Method 9 Densities -- Frame 288

Figure 34. Polar Map of Fluidization Density Estimates Using Average of Eighteen Method 9 Densities -- Frame 295

Figure 35. Polar Map of Fluidization Density Estimates Using Average of Eighteen Method 9 Densities -- Frame 315

Figure 36. Fluidization Pixel Density Estimates Using Twenty Method 9 Averages Per Ring -- Frame 280

Figure 37. Fluidization Pixel Density Estimates Using Twenty Method 9 Averages Per Ring -- Frame 288

Figure 38. Fluidization Pixel Density Estimates Using Twenty Method 9 Averages Per Ring -- Frame 295

Figure 39. Fluidization Pixel Density Estimates Using Twenty Method 9 Averages Per Ring -- Frame 315

Figure 40. Polar Map of Fluidization Density Estimates Using Average of Eighteen Method 9 Densities -- Frame 335

Figure 41. Polar Map of Fluidization Density Estimates Using Average of Eighteen Method 9 Densities -- Frame 345

Figure 42. Polar Map of Fluidization Density Estimates Using Average of Eighteen Method 9 Densities -- Frame 355

Figure 43. Fluidization Pixel Density Estimates Using Method 1 -- Frame 288

Figure 44. Fluidization Pixel Density Estimates Using Method 2 -- Frame 288

Figure 45. Fluidization Pixel Density Estimates Using Method 3 -- Frame 288

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