PREDICTING BOILER EMISSIONS WITH NEURAL NETWORKS

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PREDICTIVE EMISSIONS MONITORING SYSTEMS ARE ATTRACTIVE ALTERNATIVES TO MORE TRADITIONAL CONTINUOUS EMISSIONS MONITORING SYSTEM APPROACHES. THEY CAN OFFER ACCURATE AND RELIABLE MONITORING WITH POTENTIALLY LOWER PURCHASE, INSTALLATION, AND MAINTENANCE COSTS.

As federal and state emissions standards become more stringent, pulp and paper mill managers face important decisions concerning the methods and technologies they will use to meet environmental regulations. A combination of hardware analyzers commonly known as continuous emissions monitoring systems (CEMS) generally provide direct measurements of emissions. Now it is possible to infer stack gases indirectly with a software approach called predictive emissions monitoring systems (PEMS). Since most monitors offer optimum performance for particular applications, the choice of technology is important. Effectiveness and implementation costs vary depending on use.

IN SITU ANALYZERS

CEMS commonly measure boiler stack emissions in the pulp and paper industry. Although these systems may use various sensors and technologies, all designs use some form of sampler, analyzer, and data reporting capability. The actual analyzer technology depends on the gas components undergoing monitoring. Most analyzers employ an optical measurement.

The technology of CEMS offers a broad range of measurement with ever improving accuracy. Such systems are expensive to purchase, install, and maintain. This high ownership cost is driving the search for more cost-effective emission monitoring tools to meet state and federal regulations.

PEMS AS ALTERNATIVES

PEMS are alternate air monitoring methods gaining wide acceptance. Sometimes called alternate continuous emissions monitoring, this method of emissions monitoring uses mathematical modeling techniques applied in powerful software engines.

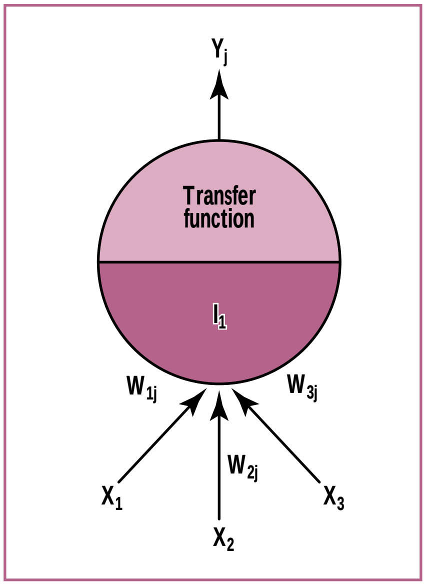
Rather than measuring stack emissions directly, PEMS infer these emission measurements through relationships with other known process parameters. PEMS therefore can determine stack contaminants in real time by correlating emissions with key combustion unit parameters like fuel type, air and fuel flows, combustion temperatures, etc. The existing 40CFR75 Subpart E—acid rain rules—already allows use of PEMS under the proposed cluster rules for total mill emissions. Many states already have legislation in place or pending to allow PEMS as measurement methods.

PEMS IN PULP AND PAPER MILLS

A typical integrated pulp and paper mill has power boilers, recovery boilers, and perhaps a hog boiler. Not all types of boilers are good candidates for PEMS.

Improving recovery boiler operations is always an interesting challenge. For several reasons, PEMS will not perform well on a recovery boiler. The most important reason relates to the complex reactions that occur as liquor droplets fall onto the smelt bed during the burning of black liquor. Other complicating factors are varying levels of sulfur in the black liquor, droplet size variation, differences in reduction efficiencies, black liquor solids, black liquor organic to inorganic ratio, air distribution, and the changing shape of the char bed. All these variables can affect the emission output from the recovery unit. They are difficult or impossible to measure. Recovery boilers are therefore not good applications for predictive models based on neural networks.

Hog boilers offer a similar challenge. It is impossible to accurately measure bark from different species with



1. Illustration of the thought process

varying moisture contents. This factor and the types of foreign materials that typically find their way into a hog boiler prevent the neural network from identifying consistent relationships from which to "learn." It is also important to obtain data over a broad spectrum. For these reasons, good correlations between the actual process and the neural net predictions are difficult to achieve.

Power boilers are usually good prospects for PEMS. Measuring the subtle variations in a single fuel boiler is most suitable for an accurate, cost-effective emissions predictor in the mill.

An actual application involving the monitoring of NO_x from a 150,000 lb/h gas fired boiler provides a good illustration of the accuracy of neural network PEMS. In operation for over one year, the operation uses conventional CEMS. The correlation between the neural net predictions and the actual measurements from the hardware analyzer exceeds 95%.

While this level of accuracy is impressive, it is important to recognize that accuracy over time depends on sufficient range of the training data, stability of the process, and process modifications. For example, there was an adjustment of the physical location of the burners on the boiler. The accuracy of the model decreased to 88%. After retraining of the model using data collected with the new burner locations, the prediction accuracy returned to approximately 95%.

METHODS OF DEVELOPING MODELS FOR PEMS

The most common technologies used for predictive emissions monitoring are first principles models and artificial neural networks. First principles models of PEMS use physical and chemical relationships such as reaction kinetics, material balances, and thermodynamics. Equations that approximately correlate emissions with combustion thermodynamics and kinetics have been available for decades. Recent regulations have encouraged further research in this area to improve the accuracy of first principles models. The main disadvantage of this technology is the impracticality for the typical mill engineer to develop and maintain these models. Developing an accurate first principles model requires much empirical research and process knowledge to provide data relationships over the normally wide range of operating conditions.

Many first principles PEMS require tuning for the particular unit they are modeling. This tuning typically involves starting at a standard combustion unit load baseline and then making incremental load changes to monitor how the response of a particular unit varies from the baseline. One then incorporates the variability from the baseline of a particular unit into the emissions model using adjustable coefficients. Even with proper tuning, first principles models also may be inaccurate when ambient conditions are extreme or when the combustion unit itself changes over time.

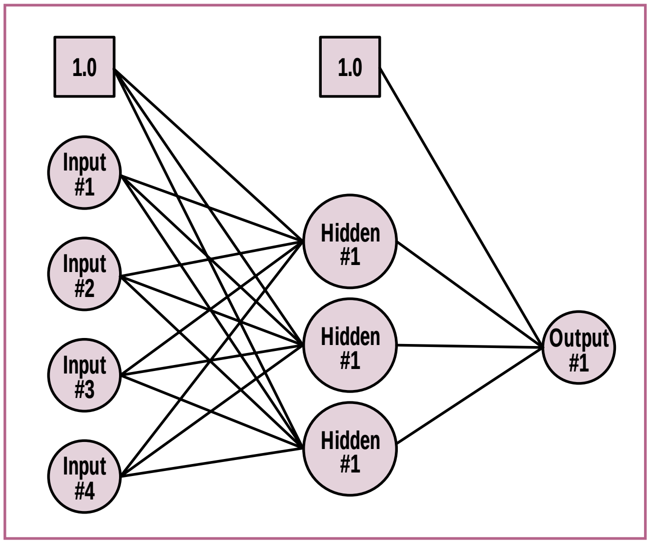
NEURAL NETWORKS: MODELING THE HUMAN BRAIN

Artificial neural networks offer a different approach to modeling. They are probably the most promising method for predicting the behavior of power boilers and their emissions. This technology uses the term artificial neural network because the control software attempts to mimic how the human brain reacts to information in making decisions.

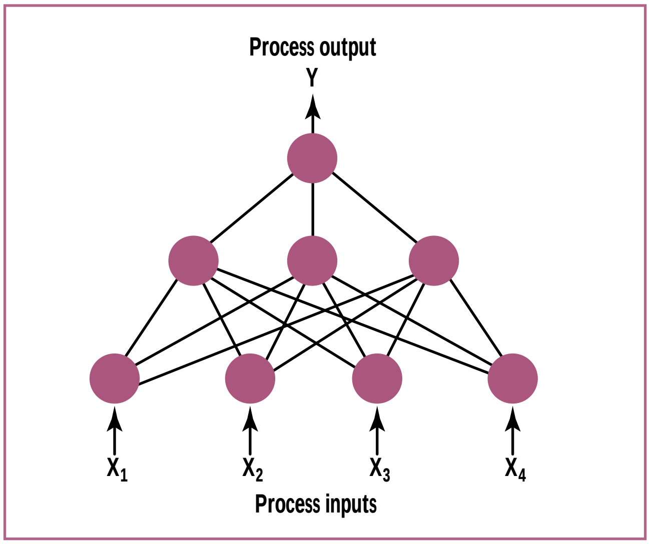
This is a reasonable analogy, although a software representation is much simpler than the complex brain. For example, the human brain has billions of brain cells or neurons that can form trillions of connections influencing behavior and response. Neurons function using their physical structure to create an output response of the following description:

- A cell body containing the nucleus for signal processing
- Dendrites that act as impulse data or input channels
- An axon that conducts the neuron output signals
- Synapses that transmit signals from one axon to the dendrites of another neuron.

In the human brain, inputs to the dendrites have specific weighting—some input channels are stronger than others. The cell nucleus evaluates the effects of such weighting on inputs. If the sum of the inputs from the dendrites exceeds a certain threshold electrical signal, the nucleus will activate the axon to send a certain electrical charge through its synapses to other neurons. Complex human thoughts come from the processing action of billions of neurons.



2. Simple representation of neural network used in PEMS



3. Use of four process inputs to determine a process output

The inability to approximate this thought process with traditional mathematical equations produced the concept of artificial neural networks. Like a natural neuron, an artificial neuron must evaluate inputs and determine the strength of each. The artificial neuron also calculates a total of the weighted inputs and compares that total to some threshold value. The artificial neuron then determines an appropriate output value.

Figure 1 illustrates the thought process. For every pass through the transfer function, a weight, W, multiplies each input, X. The sum of the weighted inputs then passes to a transfer function. The specific transfer function will vary with each individual model. It will usually be a nonlinear function that approximates the particular process undergoing modeling. The resulting transfer function next passes to other simulated neurons for processing. A collection of these artificial neurons is a neural network.

There are many types of neural networks. The network of **Fig. 2** is a simple representation of those typically used in PEMS. This type of network is a three-layer network. It has an input layer, a middle or hidden layer, and an output layer. The network is three-layer, feed forward because no signals go to other neurons within the same layer or back to any previous layers.

Understanding the architecture of artificial neural networks is helpful to realizing their application to emissions monitoring applications. Although there can be many inputs to the neural network, the example in **Fig. 3** shows four that are pertinent to the combustion process. These inputs undergo multiplication by weighting factors, summation, transformation with a transfer function, and forwarding as inputs to the three neurons in the middle or hidden layer. The hidden layer also applies a transfer function and sends outputs for weighting, summation, and transformation to yield an output, Y. Here it might be a prediction of NO_X, SO_X, or CO.

This approach differs considerably from a first principles modeling approach that leverages mathematical regressions to develop an approximate arithmetic fit of the process. Neural networks are unique because they determine the distinct relationships between variables from actual historical data without the necessity of optimization for solving higher level mathematical problems. Proper neural network applications excel at pattern recognition and corresponding associations. This ability to discern patterns in data is "learning."

TRAINING REQUIRED

For a neural network to learn, it must undergo "training" to learn the combustion process dynamics accomplished through many training epochs. An epoch is one complete pass through the network—forward and back again—of all the time-synchronized data sets taken from the process. These can number in the thousands. Note that each data set has many variables that are important to determining the emissions output information. Most of this data comes from the process control system. There also must be simultaneous collection of the stack emissions output. Portable monitoring equipment usually senses and compiles this. The net itself undergoes training with sufficient data to recognize the unique patterns in emissions data that are often too subtle for traditional mathematical approaches to discern.

The fact that hardware emission analyzers are necessary to collect the data needed to train the net may seem redundant to the whole purpose of predicting emissions. EPA guidelines require that mills employ outside stack testing firms to check periodically the stack emissions at various load levels. There is usually no duplication of equipment or additional testing required.

Building a neural network with a packaged software tool kit typically involves three steps:

- Data collection and preprocessing
- Network training
- Network verification.

Because the quality of the data set used to train the model will determine its accuracy, the first step is the most important. A good data set for neural network training will include enough diversity to show all expected ranges of operation of the combustion unit. Generation of good NO_x and CO models has used as few as 4000 data records. This is approximately one sample per minute for three days.

During the data collection period, the mobile stack tester collects and stores electronically the data for emissions. The combustion unit control system collects data for other combustion parameters such as fuel flow, fuel to air ratio, stack draft, etc. It often is not immediately obvious which process parameters will correlate with stack emissions. It therefore is far better to collect too many different process parameters than too few. After data collection, the important next step of data preprocessing is necessary. This is a critical step because the statistics of thousands of data points indicate that there will be many outliers and data anomalies to eliminate. This is where the tools of the neural net software are handy. If there is improper data preprocessing, it is difficult or impossible to obtain accurate predictions.

Iterative epochs train the neural network to determine the best weights that will then yield the most accurate model outputs. The software tool kit can set the initial weights randomly or intelligently. Until recently, it was cost prohibitive to converge on the optimal set of weights for a particular data set. This made the application of neural networks cost prohibitive. It was due to the immense software algorithms and powerful computer hardware necessary to solve this multidimensional problem. With advances in computer hardware and neural network software, an engineer with a personal computer today can train a neural network to monitor emissions in only a few hours.

ISSUES FOR CONSIDERATION

This paper has already noted some advantages and disadvantages for using neural network PEMS vs. first principles PEMS. A more common issue that mills must determine is whether to use PEMS or the more conventional CEMS. Although there is no simple answer to this question, one must consider certain issues. The following are the most important differentiating items to consider:

- State regulatory climate
- Cost to implement
- Complexity of the application.

State regulations can be critical to the decision about which monitoring technology to use. Many states do not endorse the use of PEMS. The list of states that do allow PEMS is growing and includes Texas, Louisiana, Oklahoma, Delaware, and Arkansas. Many other states currently have legislation pending or under evaluation.

In evaluating cost, one must consider the total outlays including purchase, installation, and maintenance. Purchase costs for models of PEMS must include the necessary software for building and developing a neural net. Hardware for a computer, control system, or both may also be necessary.

Different types of PEMS use different software environments. Hardware includes Unix work stations, personal computers, and distributed control system controllers. The choice of operating environment usually depends on where computing capacity is available. Software costs also vary considerably depending on the functionality provided and the licensing terms of the vendor. Most PEMS installed on a combustion unit can model several relevant emissions.

Purchase costs for CEMS also will vary considerably depending on type. They are typically more expensive. This is because most CEMS require a separate analyzer for analysis of each emission component. Some CEMS are very elaborate with specialized probes, heated sampling hoses, chilling units, programmable logic controllers to assist in automatic calibration, and other peripherals necessary to ensure accurate sampling.

Implementation costs are a large consideration. They will vary considerably depending on the type selected. For PEMS, the installation costs may include the cost of stack testing, data collection and preprocessing, and model tuning or training. For typical neural network PEMS, costs can approach US$ 15,000. This is usually less than most CEMS installations. CEMS require periodic calibration that can lead to maintenance costs of US$ 10,000–20,000 per year when done manually. Some CEMS have automated calibration capability, but they are much more expensive to purchase.

Maintenance costs for PEMS reflect their technology. Daily calibration of PEMS is usually unnecessary. After training, their accuracy rarely degrades unless the combustion unit exhibits behavior for which the model did not undergo tuning or training. Due to variations in technology of PEMS, some states require additional relative accuracy testing for PEMS that could translate into more frequent stack testing. The particular state or local requirements for relative accuracy testing on CEMS vs. PEMS will usually determine which approach has higher maintenance costs.

Adding purchase costs, installation costs, and maintenance costs, the cost analysis will often favor PEMS. Costs vary widely depending on the particular technology chosen.

The complexity of the application is the third major consideration in deciding whether to apply PEMS or CEMS. As with CEMS, federal and state regulations require that PEMS demonstrate a high degree of accuracy and reliability over a wide range of operating conditions. For very complex applications, the cost of developing models to meet these regulations can exceed the break-even point. This would negate use of CEMS. Even the most advanced modeling techniques have limitations that will restrict their application in complex situations like hog boilers where the mix is highly variable.

Using CEMS or PEMS is not mutually exclusive. Combining PEMS and CEMS on the same application provides very high monitoring uptime for important emissions applications at a small incremental purchase cost compared with using CEMS alone. With CEMS permanently installed, the training and tuning costs and relative accuracy testing costs of PEMS can be drastically lower. This is because stack testing will be necessary less frequently.

CONCLUSION

CEMS and PEMS offer effective emissions monitoring that can help achieve compliance with state and federal legislation. The high costs of compliance will continue to drive industry to search for cost-effective ways to monitor emissions. When properly applied, PEMS provide an alternative to more traditional CEMS approaches by offering accurate and reliable monitoring with potentially lower purchase, installation, and maintenance costs. **TJ**

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