

Model-based emission monitoring

PEMS: a monitoring system that uses artificial intelligence to reduce environmental impact

NUNZIO BONAVITA, FEDERICO CALLERO – Acquiring proper, reliable and timely information about actual emission levels is crucial in order to deploy adequate control actions to keep emissions inside law-enforced limits. This, combined with the need to comply with the ever-increasing demands coming from regulatory bodies, means process industries have started to equip themselves with Environmental Management Systems (EMS) that monitor, collect and process environmental data. In principle several types of monitoring systems are available but the most efficient and reliable one is the Continuous Emission Monitoring System (CEMS), where a continuous stream of data is acquired by rapid-response instruments and displayed in real time. Recently, another system, known as the Predictive Emission Monitoring System (PEMS) has been attracting attention. A PEMS uses an empirical model to predict emission concentrations based on process data, and it has been successfully implemented as part of a comprehensive EMS in one of the largest gas processing plants in the world.



ccording to ISO 14001, the goal of an Environmental Management Systems (EMS) is "to enable an organization to establish, and assess the effectiveness of procedures to set an environmental policy and objectives, achieve conformance with them, and demonstrate such conformance to others" [1]. In accordance with this, a typical EMS is designed to provide a number of functions, including:

- Collecting and processing environmental-related data
- Providing key environmental performance indicators
- Providing environmental performance evaluation planning
- Emission calculation and reporting
- Record keeping and audit trail functionalities

A well-known and reliable monitoring system is the Continuous Emission Monitoring System (CEMS), which is composed of sample extraction and transport hardware, an analyzer, and data recording and processing hardware and software. CEMS can be broken into three types of methods $[2] \rightarrow 1$:

- Extractive, which involves the physical extraction of the sample from the chimney stack
- In-situ instrumental, which are automated instrumented techniques employing various detection principles for continuous or periodic emission measurements
- Parameter-based methods are possible alternatives to the installation of conventional CEMS

They are two classes of parameterbased methods: surrogate and predictive. Surrogates may be used to determine the compliance of a source with the emission standard. However, acquiring the parameter values usually requires extensive testing and validation. On the other hand, predictive parameters are applied in cases where the relationship between process conditions and emission levels is such that it cannot be properly described by a single parameter. Predictive class parameters involve the concept of modeling, which nowadays plays an important role in emission management systems \rightarrow 2.

A Predictive Emission Monitoring System (PEMS) – also known as an inferential analyzer – cannot measure emissions directly but uses an empirical model to predict emission concentrations based on process data, such as fuel flow, load, operating pressure and ambient air temperature. In fact PEMS can provide the only way of obtaining a continuous stream of (estimated) emission values in process units where CEMS' are not present and where either in-situ (ie, periodic) analysis or the campaign approach is implemented. In such cases the plant is allowed to lease a portable CEMS to

Title Picture

Statoil's liquefied natural gas (LNG) plant at the island "Melkoya" near the city of Hammerfest, in northern Norway. ABB has delivered a complete range of power and automation products and systems to this gas processing plant. Gas from the "Snohvit" (Snow white) gas field is recovered through subsea templates, transported in pipelines to the plant, where the gas is cooled down until it becomes liquefied and ready for transport by ship.

1 Typical continuous emissions monitoring system (CEMS) configurations



Acquiring proper, and reliable information about emission levels is crucial if adequate control actions to keep emissions inside law-enforced limits are to be deployed. gather sufficient emissions data to build and validate the models. Once the models have been certified, the CEMS is removed and replaced by the inferentialtype system [4]. PEMS can also be used as a back-up if a CEMS is in place, and irrespective of which role it plays, it provides numerous benefits in different applications \rightarrow 3.

Many applications have proven that software systems are just as accurate as the hardware-based CEMS. In addition, virtual analyzers offer other functionalities that can [5]:

- Identify the key variables that cause emissions
- Automatically validate sensors
- Reconstruct emission levels from historical data when the hardware device fails
- Complement and enhance process optimization strategies

Actual regulation requirements insist that periodic tests need to be performed at the stack as well as continuous emission monitoring in order to prove compliance with the legal limits and track eventual violations. A conventional CEMS, however, cannot anticipate pollutant limit violation. A PEMS, on the other hand, could allow plant engineers to directly correlate the relationship between varying operational parameters, predict plant emissions in advance and take action to adjust emissions before violations occur. The mood around the world regarding the methods used to monitor emissions is changing: Many European regulations now explicitly call for software-based redundancy emission monitoring systems while in the US, several states allow artificial intelligence (AI) technologies based on models like PEMS as an alternative monitoring technique.

Underlying technology

As a mainly software analyzer, the successful implementation of PEMS depends largely on a powerful model-building and model-implementation tool. This tool has to ensure the availability of efficient and reliable modeling technologies together with all the required functionalities for data acquisition, data processing, model testing, etc.

One such tool, the Inferential Modeling Platform (IMP), is an innovative ABB proprietary software package for the development and deployment of data-driven advanced applications. IMP is based on two separate environments:

- IMP Model Builder for application design and development
- IMP Online for online project deployment and monitoring

The IMP features the latest generation of data analysis and modeling-building technologies (eg, neural networks, genetic algorithms, multiple linear regression, calculation scripts) including Alderived algorithms and tools, all of which can exploited through a broad collection of highly sophisticated tools [6]. These tools are embedded into an intuitive working environment based on the latest HMI concepts. The IMP is loaded onto a PC that communicates through OPC with the distributed control system (DCS) containing the process variables and analyzer data (if PEMS is used as a backup). Using real-time process data, the models output the estimated value of the relevant emissions, which can be either monitored via a dedicated HMI or sent back to the DCS operator interface.

Modeling is used to develop compact mathematical expressions that describe the behavior of a process or equipment. There are two main approaches: theoretical and empirical [3]. A theoretical model is derived from scientific principles, such as the conservation of mass and energy, and the laws of thermodynamics, while an empirical model is mathematically derived from plant-specific process data. In general, modeling is able to provide an accurate real-time estimate of difficult-to-measure quantities; exploit otherwise hidden or neglected correlations; and provide a deeper insight into the process. Estimated quantities are often referred to as inferential variables and the model is also called an inferential model. Advanced process control strategies usually employ inferential models.

The relationship between the input data (ie, available measured variables) and output data (ie, the variable that needs to be estimated) is determined during the model building stage. Dedicated software is used to import, pre-process and filter out historical datasets, which must include all the possible samples of the quantity that needs to be estimated. The resulting model has to be extensively tested and validated on the widest possible range of operative conditions. When this is completed, the model can be placed online where it is fed with real-time process data. This data is generally pre-processed to identify transient states and filter out possible outliers and bad qualities. The model output is also pre-processed to increase its reliability and accuracy.





PEMS at work in industry

In 2007, ABB was awarded a contract to supply a comprehensive EPA-compliant EMS for a primary plant of a major gas provider in the Gulf region. The plant, one of the largest gas processing plants in the world, has eight gas-processing trains and two gasinjection trains with a feed gas capacity of 3,500 billion standard cubic feet per day. The plant produces network gas, natural gas liquids (NGL), condensate and sulphur. The project required the installation of CEMS (on a temporary basis), PEMS and a dedicated data acquisition system to provide emissions measurements to ensure health and safety compliance and for process improvement purposes → 4.

In the field, the two gas-injection trains, A and B, are configured in parallel and each has two two-stage axial compressors, C101 and C102 → 5. Each compressor is driven by a gas turbine (GT), whose emissions are monitored by a PEMS. Sales gas is used to drive the high-pressure (HP) and low-pressure (LP) stage turbines. The HP turbines operate in all cases at constant speed, ie, very close to 100 percent of the maximum speed. The speed of the LP turbine can vary depending on the plant operating conditions, but it is mainly dependent on the availability of sales gas. In most cases the two trains are operated together, close to their maximum load. However, during times of little or no gas production, one of the two trains is operated at a lower load or speed. In summer PEMS could allow plant engineers to directly correlate the relationship between varying operational parameters, predict plant emissions in advance and take action before violations occur. 4 An overview of the required environmental management system (EMS)

5 The turbo compressor unit configurations



when ambient temperatures are very high, the overall efficiency of the system is reduced in order to reduce excessive stress on the equipment.

At this plant PEMS has a crucial role in emission monitoring as it works solely for gas turbines. To design the most appropriate model for PEMS, a temporary CEMS analyzer was used at each stack unit to acquire proper emissions data, IMP provides a user-friendly environment for applying Principal Component Analysis (PCA) \rightarrow 6, a powerful technique that allows engineers to represent and analyze the variability of the system from which they can identify a minimum subset of the most representative variables from a wider range of process parameters. Another advantage of PCA is that it identifies different process settings and abnormal operating conditions, as well

> as the mutual influence between input (ie, process variables) and output (ie, emissions).

> > Once the data processing phase was completed, a set of around 1,700 records (ie, a set of

The EPA assessment and certification process required 18 test runs lasting 30 minutes each at two different operating conditions.

while simultaneously process data were collected directly from the plant DCS through an OPC protocol. Data collection lasted about six weeks to cover the widest range of process conditions. Model design and validation, data processing and site implementation activities were executed using ABB's IMP. Data processing is a key step during the development of an empirical model. To begin with, both the input variable set and optimum pattern for the plant model were defined using sophisticated statistical and mathematical techniques. Identifying the optimal sampling rate for modeling purposes was critical because it has to satisfy two purposes: allow the identification of process dynamics and conditions; and provide an adequate number of suitable data sets to create good and accurate models.

process and emission values sampled on an hourly basis) and 35 variables were identified as suitable for creating effective models. Included in this dataset are:

- The main process parameters, such as air and gas inlet low, feed flow, compressor load, turbine inter-stage and exhaust flue gas temperature
- Important weather-related measurements, such as air temperature and humidity
- Pollutant emission measurements, such as NO_x, SO₂, CO, CO₂ and flue gas flow

Of the several options available in the IMP tool, feed-forward neural networks (FFNN), a powerful AI modelling technique was deemed to provide the most accurate, reliable and robust models. Each set of models was characterized by the number of hidden-layer structures, input variables such as the key process variables mentioned above and number of varying parameters. In order to avoid any over fitting and guarantee the right model robustness, the 1,700 input values were split into three subsets: training (50 percent); testing (25 percent); and validation (25 percent). A dedicated IMP feature was used to access the sensitivity of a single input variable on the estimated emission type.

The system was integrated with the DCS and the estimated emission values were configured to be written to the EMS via the serial protocol Modbus.

Results and achievements

Once installed, the system was subjected to an Environmental Protection Agency (EPA) assessment and certification process by an authorized third-party company from the United States. The process required 18 test runs lasting 30 minutes each at two different operating conditions (ie, nine at 95 percent of compressor load and the rest at 100 percent).

After each test run, the emissions estimated by PEMS were compared to the values measured by CEMS, enabling the relative accuracy ¹ of the PEMS system to be determined. As the performances for each emission were compliant with EPA regulation, the system was certified and then finally accepted by the customer \rightarrow 7.

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Footnote

1 Accuracy = \frac{1}{n} \sum_{i=1}^{n} abs (Y_i - Y_i^*)
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Where: Y_i is the PEMS estimation, Y_i^* is the actual composition and n is the number of samples used in the comparison.

6 ABB's Optimize^{IT} IMP model builder for data processing and PEMS modeling



7 PEMS project results and resulting certificate

| Property | Ra 95% Load | Ra 100% Load |
|-----------------|-----------------------|-----------------------|
| Oxygen | < 10% | < 10% |
| NOx | < 10% | ≈15% |
| SO ₂ | undetected (<1ppm) | undetected (<1ppm) |
| CO | < 10% | < 15% |
| CO ₂ | < 10% | < 10% |
| | | |



The innovative PEMS application represents the first EPA validated system based on predictive technologies in the Gulf region.

The innovative PEMS described above represents the first EPA validated system based on predictive technologies in the Gulf region, and its success is opening the way for further applications in that area. Currently PEMS technology is being tested by another major oil and gas player for government acceptance in other Gulf and Mediterranean countries. Many see the advantages of having an easily adaptable "smart" system:

- Its performance is accepted by internationally recognized environmental agencies.
- A predictive system can improve traditional CEMS availability.
- PEMS can actually replace traditional analyzers in cases where CEMS are not available or usable.

In addition to these advantages, the simulation features provided by the ABB solution allows plants to investigate possible operation improvements in a non-invasive environment and determine best practices to run the process. They also enable the advance testing of optimization systems to satisfy local environmental regulations.

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