# The better path to the Digital Twin

**Physics-based modelling is the key to the correct representation of a power plant.**

Machine learning (ML) has been a buzz word in recent years also in the power industry, but there are several reasons why the application of this technology has not been as successful as with the manufacturing and other industrial process industries.

One important fact is that power plants interact much more with the ambient than other industrial processes, simply due to the fact that the water-steam cycle must reject surplus heat from the condenser. In addition, the ambient conditions have a significant effect on output and heat rate of gas turbine-based power plants, and thus the entire range of ambient must be reflected suitably by their digital twins. Since combined cycle power plants are also among the most flexible producers, they may be dispatched over a very wide load range fulfilling the target output with varying plant configurations. The resulting abundance of possible operating modes is thus practically never covered with sufficient data in the plant historian, so that ML-based models cannot be trained to fully represent the capabilities of the plant, even more so when it comes to actual technical limits, since 'normal' operation should have some margin to such boundaries. Adding the typical scatter in plant sensors, it becomes obvious that a purely data-driven model is likely to be inaccurate, and unpredictable when exposed to exceptional – but possible situations.

**Simulated data derived from a good physical model ensure quality and completeness of information.**

Since many years, the Austrian expert company ENEXSA focusses on thermodynamic simulation of power plants, and it has developed special distributed calculation technology that allows to manage the execution of very large batches of simulations on server farms. Utilizing EBSILON heat balance models that are initially configured based on vendor data and then tuned to accurately match selected representative historical data, the power plant process can be reliably predicted over the entire range of ambient conditions and operating modes. Due to the scalability of the system, what would have taken months on a single PC can now be accomplished within minutes. With this approach, a complete and consistent set of data representing the subject power plant can be provided for the ML process.

**Why then use machine learning at all? Simply because for decision making, time is of essence.**

A well-trained neural net-based digital twin can produce the same key results as the thermodynamic model about four to five orders of magnitude faster than the heat balance software. For applications to plot accurate operating maps in terms of fuel consumption and capacity limits such as ENEXSA's Visual Operations Support tool, a single display contains tens of thousands operating points. Optimizing power plant set points for the current production target or finding the optimal schedule for day–ahead or weekly scenarios may have to evaluate even millions of options.

**The key quality criterion for ML remains: "I have seen it all"**

Whatever you want the ML-based digital twin to predict, you have to make sure that this possibility is properly represented in your learning set. You wouldn't want to actually expose your plant to massive degradation or even failures just to have them. Luckily, simulation can do the trick.


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