White Paper

ETA Cool

Proprietary Cooling Plant Optimization

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1. Cooling Plant Optimization

Cooling plants are comprised of three primary equipment types: chillers, cooling towers, and circulation pumps. Plants can range from a single chiller for a small building to over 20 chillers operating in concert for a large district cooling network. The vast majority of cooling plants are focused on ensuring operability with controls set to satisfy chilled water temperatures across the range of potential cooling loads encountered. This objective must remain the primary objective, however there are a multitude of dispatch configurations that can achieve this goal. But not all configurations will consume the same amount of electricity. The foundational premise for cooling plant optimization is the following:

> "For every operating condition there must exist a global optimum configuration that consumes the least electricity whilst still satisfying the current cooling load."

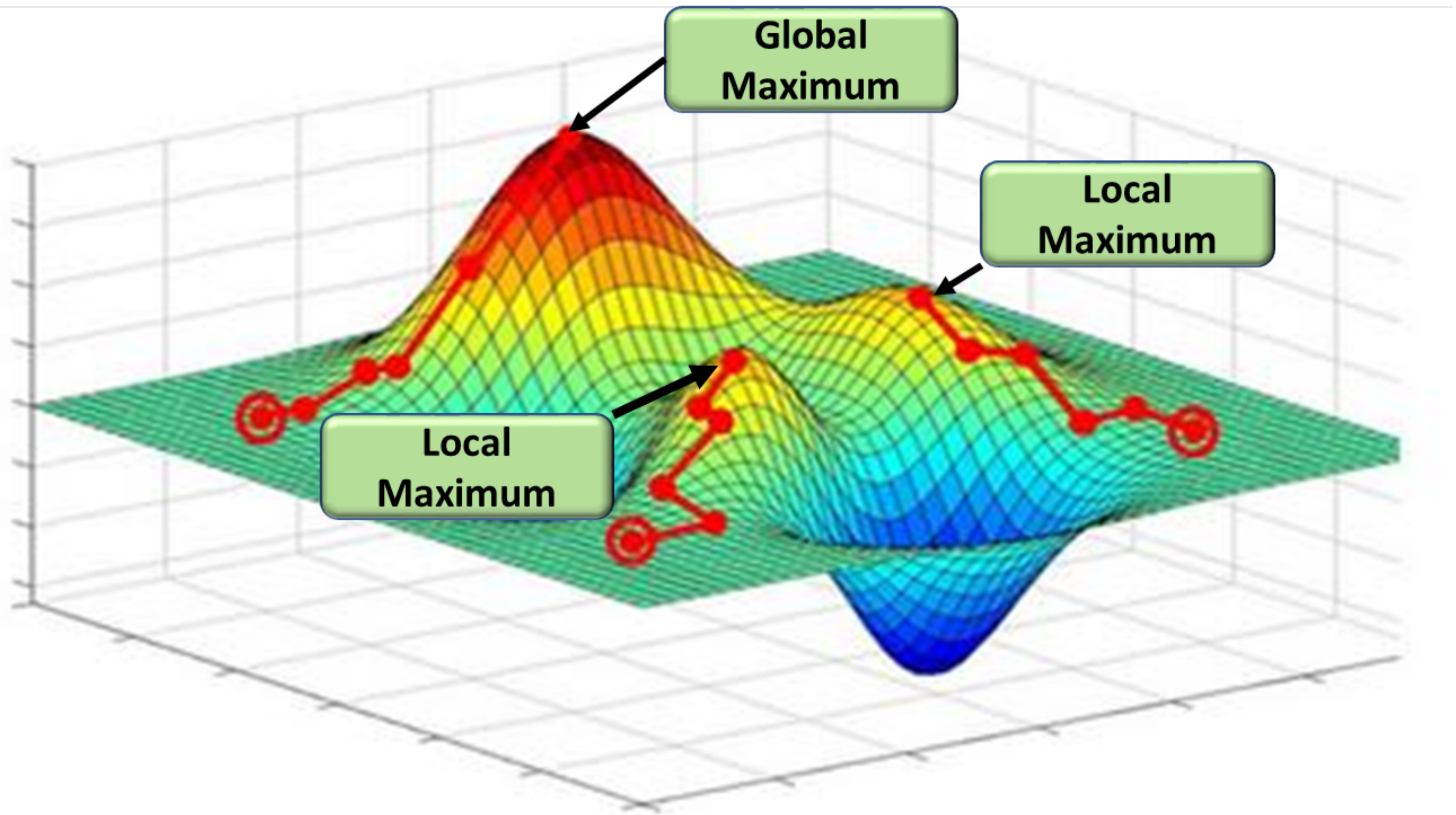
How to find this optimum configuration is the topic for a myriad of scientific theses, control system vendors, chiller manufacturers, plant operators, and mechanical engineers. The current philosophies circle around methods involving many catch phrases: Machine Learning, Cloud Computing, Big Data, Artificial Intelligence (AI). Somewhat lost in the cacophony is the tried and true approach of Model Predictive Control.

Model Predictive Control (MPC) is often challenged by proponents of Machine Learning or Artificial Intelligence because a custom model must be created for each system encountered. As there are a plethora of chiller plant configurations and flow configurations, the difficulty to develop a model for each specific combination is daunting. In theory, the advantage of MPC is that an accurate model can predict the efficiency of the cooling plant under any conceivable operating condition and thus can inform the dispatch state to drive to the current global optimum. The accuracy of the model will determine how close to the true optimum the commanded dispatch will be.

In contrast, Machine Learning and AI based algorithms continuously adjust the live system to "hunt and seek" for the optimum combination. There is an advantage to this method as it does not require knowledge of the entire system, it only needs to know if the latest change to the system was better performing than the last state. This allows these methods to constantly adjust for changes in equipment performance, configurations, and even the addition of new equipment. Model Predictive Control algorithm can also be adjusted or tuned using live performance data. An MPC algorithm based on manufacturer performance curves will match the equipment variations from manufacturing tolerances or after degradation. Thus the MPC control will not be targeting the optimum state, but a "learning" algorithm may be able to seek it out.

There is a downside to this continuous optimization with machine based and AI algorithms. These algorithms only operate the plant near the current state. This means that although they can seek for the local optimum point, they may not be near the global optimum and indeed may never learn where that configuration exists. Consider the two operational starting points below that lead only to the local maxima; from these starting points the machine learning will never find the true global maximum as they will get stuck on their local peaks.

Even when the machine learning algorithm is close to the current global maximum, it is continuously seeking the next best operational state. Using numerical algorithms, the system continuously hunts for the new optimum condition. But the very act of hunting means it operates for some fraction of the time away from true optimum.



Model Predictive Control on the other hand drives directly to what it determines (based on a complete model of the system) is the true optimum condition. If the Model is tuned to the current cooling plant equipment performance curves, then the MPC control will achieve the true global optimum directly without any delay or continuous hunt and seek error. Historically the challenge was recalibrating the MPC model to align with the current performance drift of the operating equipment.

The ideal solution would have the speed and accuracy of the MPC control with a periodic (not continuous) calibration of the model. This is the basis for the Eta-Cool algorithm.

2. Model Predictive Control

Eta Cool is a Model Predictive Control algorithm created using a software tool called TRNSYS. TRNSYS is a transient thermal analysis tool that is the benchmark for virtually all other models. At its core it is a physics-based modeling and simulation tool with object-oriented programming that accommodates any combination of chillers, towers and pumps as well as the control strategies used to operate them. A challenge with implementing Model Predictive Control algorithms is that programming different configurations is time consuming and requires expert resources.

These issues have been overcome with the creation of a generic system model that can rapidly model the majority of common cooling plant configuration. Eta Cool can model up to 10 unique chillers and 10 unique cooling towers. The two most common flow configurations are also addressed: primary/secondary and variable primary.

3. Data Acquisition

In order to function, all optimization solutions rely on data. The first step is to ensure that all relevant data points are measured and historized. For chillers, this condenses to just 4 key tuning parameters:

- Condenser Average Fluid Temperature
- Evaporator Average Fluid Temperature
- Chiller Cooling Load
- Chiller Power

For Cooling Towers:

- Fan Speed
- Tower Inlet Water Temperature (Same as Condenser Outlet Temperature)
- Tower Water Flow Rate
- Ambient Wet Bulb Temperature
- Ambient Dry Bulb Temperature
- Fan Power

For Pumps:

- Differential Pressure (aka Head)
- Pump Speed
- Pump Power
- Flow Rate

With these measurements for the individual components of the cooling plant, the performance curve for every piece of equipment can be calibrated. This allows the next steps of the optimization process to proceed.

4. Baseline Performance:

Another key element of analysis is the determination of the baseline performance of the system. Surprisingly this may be distilled to a relatively small number of parameters in order to generate a function that will accurately reflect a cooling plant's performance across the full range of operating conditions. The following 4 parameters can completely characterize any cooling plant:

- Dry Bulb Temperature (C)
- Wet Bulb Temperature (C)
- Cooling Load (kWh)
- Cooling Plant Energy (kWh)

With these measurements over a sufficient period of time, any cooling plant's performance can be accurately predicted. This is critical to the assessment of energy savings after retrofits and controls modifications have been implemented.

The topic of characterization and baseline performance measurement is well understood. There is an international protocol developed to ensure accuracy for such measurements. The International Performance and Measurement Verification Protocol (IPMVP) has been developed and defines the methodologies, methods, and acceptable error margins for the determination of energy savings relative to a systems baseline performance. Under the IPMVP the Option B approach creates and energy boundary around a subsystem of a facility in order to generate a more accurate baseline. This allows a high accuracy when determining the savings on just the cooling plant which may have been obfuscated if measured at the main electricity meter.

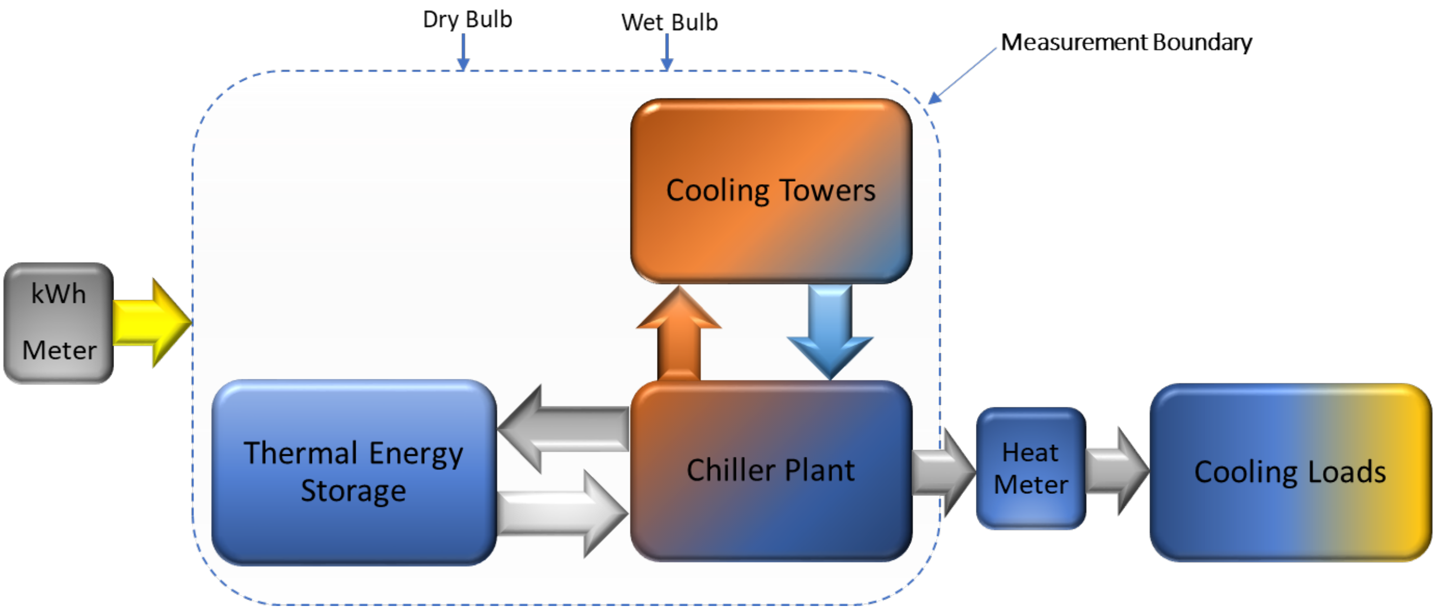


Figure 1: Baseline Cooling Plant Performance

Applying industry standard best practices allows the determination of the baseline performance typically to within a 5% accuracy and a confidence interval greater than 90%.

5. Model Predictive Control

Initially, the generic model is configured using manufacturer supplied performance data for each component of the plant. Using this data, an optimal dispatch table is generated by pre-processing every possible plant condition. The operating range or envelope for equipment is constrained as per manufacturer's specifications.

Definition of Operational Envelope:

> "The maximum and/or minimum extents for operational parameters of a given piece of equipment beyond which the equipment may shutdown, be damaged, or otherwise become inoperable and require intervention to return to operable status."

For example, the minimum condenser temperature, minimum approach between condenser and evaporator temperature, and minimum load fraction are all programmed into the model to ensure that invalid operational states are excluded from the optimization.

After sufficient data gathering from all components of the operational plant, the performance maps for individual chillers, towers, and pumps can be updated to reflect in situ performance differences from manufacturer characterizations.

The primary advantage of this Model Predictive Control is the pre-processing of the optimal configuration for every possible state of operation. For a model with 5 chillers and 5 cooling towers, the Eta-Cool algorithm will pre-process over 42 Million potential configurations. It then stores the optimal configuration for each load and ambient condition in the so called optimal dispatch table. This allows the control system to respond instantaneously to any changes in the operating system and shift the control setpoints for each component instantly to the optimal values. The plant control systems will limit equipment cycling and ramp rates according to best practices and manufacturer specifications, but these are the only limits to the speed of response system to control to the global optimum.

6. Calibration

Even new and clean performance curves for identical equipment can vary between 5 and 10 percent. After equipment is operated, there is a continuous performance drift away from starting efficiencies. There can also be sharp drops in performance resulting from defective equipment, partial equipment failures, and mal control or operational decisions. After sufficient data has been acquired regarding the performance for a given piece of equipment, the initial curves (typically supplied by the manufacturer) can be updated/adjusted to align with the newly acquired in situ performance. The differential between the previous model calibration and the newly recorded measured data can be utilized to generate actionable diagnostic alarms to trigger, predictive maintenance actions, control configuration changes, or even taking the equipment out of the current staging sequence.

The frequency of calibration will impact the system efficiency as well as diagnostic alarm management. Continuous calibration would not be recommended as calibration data sets should be sufficiently large to provide an accurate adjustment to the performance curves. This will allow a subset of the measured operational envelope to be applied accurately to the complete envelope/performance table. As typical performance drift occurs over months of operation, under normal circumstances calibrating every 3 months should be sufficient. This also allows calibration to be subdivided into seasonal operating conditions which may provide a better calibration of the operational envelope. Although calibration should only be performed periodically, actionable alarms can be generated immediately if/when the performance of a given piece of equipment is outside of normal variation for the current calibrated performance. More than 5% deviation should trigger a warning alert and more than 10% should signal urgent operator intervention is required.

The algorithm utilizes performance curves for each component of the cooling plant and preprocesses every possible load condition to determine the optimal dispatch and staging control. Modeling using a real world university campus indicates energy savings of up to 35% are achievable. Implementation of the performance monitoring also adds predicative maintenance functionality identifying underperforming equipment before a failure occurs.